Pietro Michelucci *Editor*

Handbook of Human Computation

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Introduction

A more descriptive title for this book would have been "The application, design, infrastructure, and analysis of heterogeneous multi-agent distributed information processing systems and their political, societal, and ethical implications," but as brevity is the soul of wit, I decided to go with simply *Handbook of Human Computation*.

Human computation means different things to different people. To some, it means using a computer to combine answers from many people into a single best answer. To others, it means taking a problem that is too big for any one person and splitting it into smaller, more manageable pieces that can be delegated to many people. Human computation can be the analysis of human behavior in a social network to better understand the spread of ideas or to predict outcomes on the world stage. And possibly it even represents an opportunity to recognize or engineer a new life-form with superhuman intelligence. Regardless of which of these things human computation might be, they all involve interconnected humans and machines that process information as a system, and they all serve a purpose.

What This Book Is Not

Though you will find much discussion of crowdsourcing herein, this is not a handbook of crowdsourcing. Crowdsourcing does not require computation; the term derives simply from "outsourcing to crowds." The individual contribution of each crowd member need not be computational nor give rise to computational analysis or output. Crowdsourcing is, however, a common method for engaging many participants in human computation; so they often coincide.

Nor is this a handbook of social computing. Social computing is defined as the intersection of social behavior and computational systems (Wikipedia 2013). However, social behavior is not a prerequisite for human computation. In fact, a workflow process may elicit human input, transform that input, and then pass the

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result to another human, in a pipeline that involves no social behavior or interaction whatsoever, yet is very much a manifestation of human computation. Thus, human computation subsumes social computing.

Then What Do We Mean by Human Computation?

To answer that question, we must first consider what we mean by "computation." Computation in this context refers not just to numerical calculations or the implementation of an algorithm. Computation refers more generally to *information processing*. This definition intentionally embraces the broader spectrum of "computational" contributions that can be made by humans, including creativity, intuition, symbolic and logical reasoning (though we humans suffer so poorly in that regard), abstraction, pattern recognition, and other forms of cognitive processing. As computers themselves have become more capable over the years due to advances in artificial intelligence and machine learning techniques, we have broadened the definition of computation to accommodate those capabilities. Now, as we extend the notion of computing systems to include human agents, we similarly extend the notion of computation to include a broader and more complex set of capabilities.

With this understanding of computation, we can further generalize our notion of human computation to encompass not only computation by an individual human but also machine-mediated computation by groups of individuals (e.g., pipelined problem solving systems), aggregate analytic results by groups that result from individual information processing (e.g., prediction markets), distributed networks of human sensors (e.g., mash-ups), and many other varieties of information processing that derive from the computational involvement of humans in simple or complex systems.

While this is what is meant by human computation for the purpose of establishing conceptual guideposts for this handbook, it is itself among the directives of the handbook to not only formally define this space of research and practice but to explore the past, present, and future scope of this frontier.

Why Is Human Computation Important?

Each of this book's many contributors may have a distinct answer to this question. My short answer is the following. As a species, we face multifarious challenges stemming directly and indirectly from our use of technology, and many of these challenges pose an existential threat to humanity. I believe that one promising avenue of recourse is to use technology to help us cooperate more effectively to solve the problems we have created. Thus, I believe our very survival depends upon the

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rapid advancement of human computation as a theoretical and applied science, to help us mitigate the effects of climate change, cure disease, end world hunger, protect human rights, and resolve conflicts.

Synopsis of Sections

Though the high-level structure of the book is ordinal by design, the following section synopsis will help point the reader who has specific areas of interest to the section of most immediate relevance. For the armchair reader, you may embark on a guided tour of human computation by beginning at page one. But if you happen to have a mercurial spirit, just open the book to a random chapter and see where that might lead you.

Foundations

The foundations section, edited by Matthew Blumberg, seeks to cast new light on the subject matter by asking basic questions, like “What is thinking?” “What is information?” and even “What is mental disease?” Answers come in novel forms that recast the interrelationship of foundational disciplines toward a deeper understanding of human computation.

Applications

The applications section, edited by Haym Hirsh, seeks to convey the value proposition of human computation by examining recent examples of how people have been brought together in new ways to achieve desired outcomes. This section surveys a broad range of human computation applications, in domains such as disaster relief, archaeology, medicine, science, education, literature, finance, innovation, business management, and others.

Techniques and Modalities

This section, edited by Kshanti A. Greene, catalogs an expansive and growing list of human computation techniques – that is, repeatable methods defined jointly by their applications, interaction paradigms, and/or computational methods. It is essentially a set of “design patterns” for human computation that facilitates modeling a new HC system on prior work.

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Infrastructure and Architecture

The infrastructure and architecture section, edited by Michael Witbrock, seeks to balance the logistics of humans as computational resources with goals of actualization and empowerment. Thus, it covers the broad space of computational structures such as state space, communication protocols, human device drivers, reward structure programmability, as well as HC-specific interaction modeling techniques that are sensitive to the quality of human experience.

Algorithms

This section, coedited by Remco Chang and Caroline Ziemkiewicz, describes a variety of "systematic and general ways to treat humans as computational units" as well as new methods for formalizing the properties of human computation algorithms. Thus, this section may be useful for assessing, identifying, and constructing algorithms to fit specific use cases.

Participation

This section, edited by Winter Mason, explores a range of factors and associated techniques that influence the decision to participate in human computation activities. Importantly, it also considers dynamics that affect the quality of participation.

Analysis

This section, edited by Kristina Lerman, considers several analytic methods that can be used to predict emergent collective behavior and to inform the design of future human computation systems. These analytic methods are also considered in the context of quality control and performance assessment.

Policy and Security

This section, edited by Dan Thomsen, examines near-term ethical, regulatory, and economic considerations relevant to the emergence and growing prevalence of human computation and associated labor markets. It also delves into security and

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privacy issues germane to HC systems, along with relevant technical and policy-based solutions.

Impact

The impact section, which I had the privilege of editing, is a collection of forward-thinking essays on the near- and long-term implications of human computation on individuals, society, and the human condition. It asks hard questions and considers carefully the potential risks and rewards associated with the advancement of this new technology. It attempts to characterize a future with pervasive human computation and considers how we might prepare for it.

Bon Voyage!

Whatever your interest in human computation might be, by reading from this book you will hear from a coalescent community of communities and perhaps begin to understand our place in the world in a new way.

Fairfax, VA, USA Pietro Michelucci

Reference

Wikipedia (2013) Social computing. In: Wikipedia, the free encyclopedia. Retrieved from http://en.wikipedia.org/w/index.php?title=Social_computing&oldid=553413728

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Part I
Foundations

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Foundations in Human Computation

Matthew Blumberg

The current state-of-the art in Human Computing all too often involves large batches of some mundane but nevertheless computationally intractable problem (find the blue dot; read the words; fit the puzzle pieces); and is undertaken by a developer who realizes that large numbers of people might by various means be induced to each perform modest numbers of these tasks before getting bored and moving on to something else. And if enough people can do enough of these tasks useful things can be accomplished.

But this section—and this *Handbook* generally—seeks to encourage thinking beyond such a "Virtual Sweatshop" model; and to replace it with the aspiration to create massively large scale thinking systems, systems which might some day be used to address problems at an order of complexity beyond the competence of any individual person.

Moving in this direction—opening this avenue of investigation—involves giving thought to some basic ideas: what is computing? What is thinking? What is information? This direction benefits from ideas about the nature of communication; about complex systems and the emergent properties of such systems; about control of complex systems. Ideas about networks, about collaboration, about minds, about ecosystems, about culture—and a great many other topics.

In many of these instances, the best and deepest thought has been done in domains which might on their face seem distant from software development: Epistemology, Psychology, Cybernetics, Biology, Anthropology, Economics, and so on.

This chapter is not in any sense a comprehensive collection of "Foundational" concepts; it is more a diverse set of interesting tidbits, a taste. We aspire to continue an ongoing flow of such illuminating ideas as a regular feature in a forthcoming *Human Computation* journal. But the chapters that follow embody some introductory discussions:

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Patterns of Connection (Matthew Blumberg)—Drawing on ideas from Marvin Minsky, this chapter explores the nature of Mind, and the extent to which Mind emerges from particular patterns of connection. This is used to illustrate the concept of "Cognitive Architecture", which is proposed as a central concept in Human Computing.

The History of Human Computation (David Alan Grier)—The idea of organizing groups of people to perform cognitive work precedes computers and the Internet. This fascinating chapter traces the origins of these ideas back to Charles Babbage's early analysis of factories at the dawn of the industrial era.

Biological Networks as Models for Human Computation (Melanie Moses, Tatiana P. Flanagan, Kenneth Letendre, G. Matthew Fricke)—Notions of Mind have traditionally reflected to the technology of the day; advancing technology has lead, curiously, to ever more powerful metaphors. At various points, the mind was a garden, a factory, a computer. Recent trends return to biology: this chapter explores biological networks as an instructive model.

From Neural to Human Communication (Linda Larson-Prior)—If one wants to learn to organize a thinking system, a natural place to look to for guidance is the brain. This chapter considers both neural and human communication in order to better understand the potential for computation as an emergent behavior of a system.

Pathology in Information Systems (Pietro Michelucci, Matthew Blumberg)—Mental Illness in Humans can be viewed as a specific case of the more general phenomena of pathology in information systems. Thus Human Computing systems—and groups of people generally—may become pathological: large scale political failures like the Inquisition or Fascism being an example; as potentially are smaller scale systems like dysfunctional families. This chapter speculatively explores these issues, proposing this as a domain for future inquiry, so as to develop means to prevent, diagnose, and repair such systemic pathologies—i.e., to develop means to debug complex systems.

Information Theoretic Analysis and Human Computation (Carlos Gershenson)—This chapter introduces concepts of Information Theory in the context of Human Computing systems. What is Information? What is Computing? How does one talk about Networks?

Epistemological Issues in Human Computation (Helmut Nechansky)—The field of Epistemology brings to bear centuries of thought about the nature of Knowledge. This chapter takes as a start the view of Knowledge as "an individual model of an external world", and explores the use of such models for decision-making. Implications for Human Computing are considered.

Synthesis and Taxonomy of Human Computation (Pietro Michelucci)—As this *Foundations* section demonstrates, a wide range of fields contribute to the growing body of work in human computation. Each field, though, has its own set of concepts and associated words (e.g., social computing, distributed thinking, crowdsourcing, etc.) This chapter draws from these various disciplines—and from the diverse contributions found in this volume—in an effort to organize the concepts and provide a common conceptual framework.

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Patterns of Connection

Matthew Blumberg

Background

My interest in Human Computation– described here as "Distributed Thinking"– dates back to 2008 and the FIFA World Cup final. The truth is (being American) I didn't watch. I only read about it the next day. It was quite a match, apparently– eventually won 1-0, on a 73rd-minute goal by Wayne Rooney of Manchester United. But what was most notable in the coverage– to me– was the comment that the match had been watched, live, by 700 million people.

A soccer game being about 90 min long, this amounts to more than *a billion hours* of human attention– focused on a bouncing ball. That's about 120,000 *person-years* of attention– compressed into 90 min.

Which raised the question: what could be done with all that cognition? Could it be harnessed for constructive purposes? What knowledge and tools and methods would be required?

Crowdsourcing

A number of web-based projects have emerged which draw on the aggregated intellectual skills of large numbers of people over the Internet. These projects represent the "state of the art" in Human Computation—exciting efforts to harness many minds in order to do intellectual work that would otherwise be impossible. A few key examples follow (there are of course many others):

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- *Clickworkers (2001)*—People were shown images of the surface of Mars, and asked to help map it by drawing circles around the craters. (Computers aren't good at this sort of pattern recognition, but people are.[1])
- *Stardust@home (2006)*—A NASA probe dragged a volume of gel through the tail of a comet; the comet particles were quite few and small, and searching for them in the large volume of gel was a challenge. The Stardust team posted nearly a million images of small sections of the volume online, and people were asked to search through these and to find characteristic tracks of particles. This collective effort considerably accelerated the search for the "needles" in the "haystack"
- *Galaxy Zoo (2007)*—People are shown images of galaxies, and asked to categorize them by visual features: spiral, disk, etc.; the goal is to build a celestial almanac. (As above, computers aren't good at this sort of image analysis.)
- *ESP Game (2003)*—Pairs of people are shown an image at the same time, and each starts typing descriptive words. When both have entered the same word, they "win" (and the system presumes to have learned a useful "tag" for use in categorizing the image).
- *Ushahidi (2008)*—People in and around crisis situations submit reports by web and mobile phones. These are aggregated (and organized temporally and geospatially), to give an accurate and unmediated view of the emerging situation.[2]
- *eBird (2002)*—Bird watchers throughout the world submit observations, creating a real-time database of bird distribution and abundance.
- *Iowa Electronic Market (1995)*—People buy and sell "contracts" in a (not-for-profit) Futures market, as a tool for predicting outcomes of elections, Hollywood box office returns, and other cultural phenomena.
- *FoldIt (2008)*—People solve 3D visual puzzles, as a means to solve problems in protein structure prediction.
- *Phylo (2010)*—People search for matching patterns in sequences of DNA, represented as strings of colored blocks.
- *EteRNA (2010)*—People solve visual puzzles related to the folding of RNA molecules

The above represents a fairly wide range of objectives and activities—thought it may be observed that all follow a certain pattern, one which is presently characteristic of what is commonly referred to as Crowdsourcing:

- In each project above, all users perform the same task repetitively (i.e., all users draw circles to mark craters, or place a pin to mark traces of comet, or find matching patterns in strings of colored blocks.)
- In most cases, the task is quite simple; it is the vast quantity that must be slogged through which requires the crowd input.

[1] Possibly of interest: see article in this volume by Jordan Crouser and Remco Change, discussing relative strengths of humans vs computers.

[2] Possibly of interest: See article in this volume on crowdsourcing disaster relief by Ushahidi founder Patrick Meier. Human Computation for Disaster Response.

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- Tasks are single-user: interaction among participants while performing the work is not required.[3]
- There is no parceling of task-type based on user expertise (At most, users of measured skill—ie users who have returned validated results—might get harder versions of the task at hand.)

In sum, with these tasks, there is no "higher level" thinking being done by the "Crowdsourcing" system. All of the tasks completed by the public (individually and collectively) could plausibly have been done by the project organizers—in most cases better.[4] The projects are really a means of collecting and applying large quantities of unskilled labor. This of course is useful; but much more is possible.

The discussion below seeks to make the case that it is possible to create "Thinking" systems—systems created of many minds, and capable of sophisticated problem solving….

Distributed Thinking

In order to contemplate what a large scale thinking system might look like, it is useful to have a notion of what *Thinking* is.

As a point of reference, consider the model proposed by Marvin Minsky in *Society of Mind* (1988). In Minsky's model "minds are built from mindless stuff".

Minsky hypothesizes that a Mind—that thinking—is made up of many small processes (which he calls "agents"); that these are simple; that they are not especially intelligent in and of themselves—And that *it is the way that these things are connected* that creates intelligence, as a sort of emergent property of the "thinking" system.

Picking Up a Cup of Tea

For example, if one wanted to pick up a cup of tea there might be several processes involved (several "agents"):

- Your GRASPING agents want to keep hold of the cup
- Your BALANCING agents want to keep the tea from spilling
- Your THIRST agents want you to drink the tea
- Your MOVING agents want to get the cup to your lips

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[3] ESP game is an exception here; sort of.

[4] A notable exception is FoldIt: In the case of FoldIt, it turned out that a public participant was unusually good at the task, better than subject area experts. This fact alone highlights the sophistication of that project. I.e., FoldIt serves to demonstrate the example that when projects are sufficiently advanced, they may draw in "savants", persons unusually good at the particular task—better in some cases than the project organizers themselves. And/or, projects may empower novel combinations of intellectual skills of persons otherwise unknown the project organizers.

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… These would all be independent processes, performed in parallel, competing for resources in various ways—and collectively producing the behavior of picking up and drinking the cup of tea.

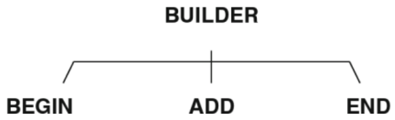
Stacking Blocks

Another illustration, a slightly more complicated cognitive problem– Imagine you had a pile of blocks, and you wanted to pile them up in a stack. You might hypothesize the existence of a "mental program" to do this, call it "Builder" (Fig. 1):

Fig. 1 **BUILDER**

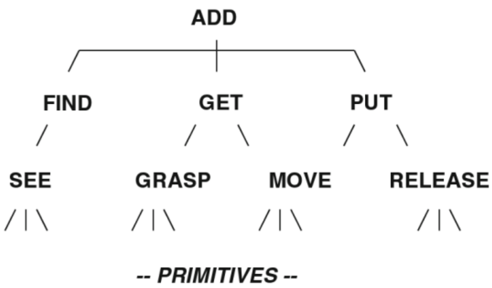
In the Minsky view of the mind, this program would be composed of smaller applications, for instance (Fig. 2):

Fig. 2



And each of these "programs" or "agents" would themselves be composed of smaller functions. And each of these, of possibly smaller… Until you got down to some list basic "primitive" functions from which all the others are built (Fig. 3):

Fig. 3



What's interesting about this approach is that if you took from the previous chart describing "Builder" only the list of the Agents themselves, you wouldn't know anything about what the Builder does. It's only when you put the things into a structure that it becomes possible to contemplate that they might do something useful (Fig. 4):

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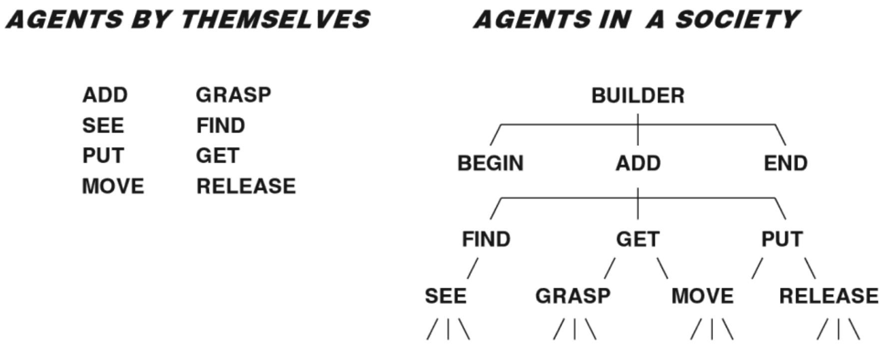

Fig. 4

This brings us to the first essential point of this essay: *Intelligence is created not from intellectual skill, but from the patterns within which intellectual skills are connected.*

The Minsky "Society of Mind" model is but one example; in general, patterns of organization which result in emergent "intelligent" behavior may be referred to as *"Cognitive Architectures"*.

From Crowdsourcing to Intelligent Systems

With an eye towards imagining a system which has a higher level of intelligence than its individual participants, and following Minsky's Cognitive Architecture– it's perhaps interesting to imagine what the set of "primitives" (the basic, unintelligent functions from which more complicated processes might be built) could be. Perhaps:

- **Pattern Matching/Difference Identification**
- **Categorizing/Tagging/Naming**
- **Sorting**
- **Remembering**
- **Observing**
- **Questioning**
- **Simulating/Predicting**
- **Optimizing**
- **Making Analogies**
- **Acquiring New Processes**

…This is not meant as a comprehensive list, just some illustrative examples. Note that none of these functions are especially complicated in and of themselves (though several are to varying degrees computationally intractable). Most are, in a wide range of contexts, quite parallelizable.

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As food for thought, consider that many of the previously listed crowdsourcing projects provide quite nice templates for several of these very activities:

- **Pattern Matching/Difference Identification—**As noted, in *Clickworkers*, participants identified circles in a database of images; in *Stardust@home*, participants identified characteristic traces of comet dust in a database of images; in a range of other projects participants mark features on satellite images to generate or enrich maps, etc.
- **Categorizing**—In *Galaxy Zoo*, participants are shown images of galaxies, and asked to categorize them, by visual features: spiral, disk, etc.—and this is used to build up a structured database of astronomical objects.
- **Tagging/Naming—**In *ESP Game* participants create useful tags for image search (*In fact the system was licensed by Google to improve their image-search functionality).
- **Observing—**In *Ushahidi*, in *eBird*, and many other projects, distributed observations are entered into a shared central database
- **Simulating/Predicting—**In *Iowa Electronic Market*, and a wide range of subsequent "Prediction Markets", participants engage in a process which has been shown to effectively predict the outcome of a range of events.
- **Optimizing—**In *FoldIt* participants are asked to optimize the shape of an object according to certain parameters.
- **Etc…**

Following the earlier discussion, while it may be the case that any individual one of these systems is useful and interesting, it is the potential of *putting these things together into systems*– into intelligent patterns, into Cognitive Architectures– where really interesting things may become possible.

A Speculative Example

Imagine creating a drug discovery pipeline using Distributed Thinking –

By way of context, note that one method of drug discovery is {1} to identify a mutant or malformed protein which has been implicated in a specific pathology. And then {2} to find some other protein that binds to this deviant but nothing else– this is akin to sticking a monkey wrench into a running machine: the goal is to muck up the works, to cause that process to fail. And this can be quite effective.

Given a target identified by lab work, one could imagine subsequently breaking the process of discovering such "monkey-wrench" proteins into a sequence of steps– like, "docking" to see what candidate proteins stick to your target; "similarity analysis" to see which proteins are like which other proteins (to find alternative avenues of exploration); "optimizing" (to improve marginally useful candidates); "cross screening" (to see if a candidate has side effects, by checking whether it docks with anything it's not supposed to); and so on… (Fig. 5).

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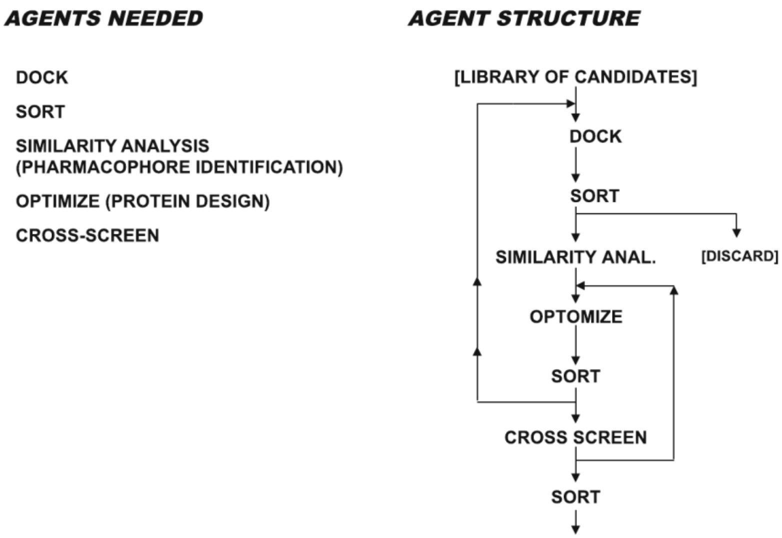

Fig. 5

All of these individual steps/processes could be imagined in terms of systems on par with existing crowdsourcing applications. And one could imagine linking these functions—these agents– into a fairly elaborate workflow,[5] the collective function of which would be to seek out and create promising drug candidates.[6]

Summary

A great deal has been done with Crowdsourcing. Current examples share a number of features however, most notably insofar as each supports only a single type of task. The discussion presents the idea of "Cognitive Architectures"—patterns into which individual systems, each performing specific (and potentially mundane) tasks, might be interconnected to collectively create a higher level of cognition.

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[5] A small but important step in the evolution from current-generation Crowdsourcing to Distributed Thinking would be adoption of a standard means to integrate individual projects (individual functions) into more complex workflows. It is hoped that developers of such projects—and especially developers of middleware like BOSSA and PyBOSSA—will provide APIs that enable others to submit inputs and collect outputs, so the output of one project might be used as the input for another. For instance, a Phylo-style DNA project might input sequences into a FoldIt style structure prediction application.

[6] Of course there are numerous technical reasons why these steps are incomplete or may be impractical or infeasible at the moment. As noted it is a speculative example, a broad-stroke illustration.

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The goal is to raise the prospect that "Apollo Project" challenges might be met by the application of sufficient attention, properly structured—It's all a matter of the patterns by which we connect ourselves and our information.

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Human Computation and Divided Labor

The Precursors of Modern Crowdsourcing

David Alan Grier

Nature of Crowdsourcing

Though it is often to be a new phenomenon, one that is deeply tied to new technology. Jeff Howe, who identified and named the phenomena, claimed that it was a revolution "intertwined with the internet." (Howe 2008) However, it is actually a very old idea, one that has many historical antecendents in the twentieth, nineteenth and even eighteenth century. To understand crowdsourcing, we need to go back to Charles Babbage, the early nineteenth century mathematician.

Babbage was perhaps the first to understand that computation of any form was merely a form of divided labor. Babbage, of course, was not the first to discover divided labor. The concept of divided labor opens Adam Smith's 1776 book, The Wealth of Nations. "The greatest improvements in the productive powers of labour," Smith wrote in his first chapter, "and the greater part of the skill, dexterity, and judgment, with which it is anywhere directed, or applied, seem to have been the effects of the division of labour."(Smith 1776)

However, crowdsourcing is not merely any form of divided labor but the single form of divided labor that is untouched by modern information technology, the division of work by skill. Traditionally, economists have identified five ways of dividing labor. Any task can be divided by time, place, person, object and skill. You can create tasks by identifying the time when it must be done, the place where it must be done, the people with whom it must be done, the object on which the work is done and finally, the skill needed for the task.(Barnard 1936) Of those five methods, the first four can be mediated by modern information processing technology.

This technology can used to move work so that it need not be done at a specific time or place. It can move data, the object on which the work must be done, from one place to another. Finally, it can also be used to establish communications

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between any team of people on any part of the globe. The one thing that it cannot do is to change the skill of individual workers, though it can connect workers with different skills to work on the same project.

Crowdsourcing moves beyond the mere division of labor by skill and looks at the problem of how to combine best the skills of workers with the capabilities of information technology. It considers how to divide work and assign some tasks in order to get the right skills doing the right pieces of the job. As such, it is an example of what production managers call "refactoring work." The current forms of work that we identify as crowdsourcing are merely ways of refactoring work in a way that can use workers flexibly and that gets the right skills to the right part of a production. Charles Babbage was among the first scholars to look at this problem and certainly prepared the foundation for crowdsourcing.

Babbage and the First Scholar of Crowdsourcing

As a starting point for the study of crowdsourcing, Babbage has a much better perspective than Smith. Smith wrote at the start of the industrial era and focused on the four forms of divided labor that are easily handled by information technology: the division of labor by time, place, person, and object. Furthermore, he had a limited understanding of the potential of machines. He wrote of machines as tools. "A great part of the machines made use of in those manufactures in which labour is most subdivided, were originally the invention of common workmen, who, being each of them employed in some very simple operation, naturally turned their thoughts towards finding out easier and readier methods of performing it." (Smith 1776)

Writing more than 50 years after Smith, Babbage had a better understanding of the division of labor by skill and the role that machines might have in such a division. Babbage is generally remembered as a nineteenth century mathematician who designed computing machines.(Hyman 1982) In fact, Babbage is a much broader scholar, who was interested in chemistry, astronomy, and economics as well as mathematics. Perhaps the best way to understand Babbage is to recognize that he identified himself as an "analytical mathematician" during his years at Cambridge University and formed a club called the Analytical Society. (Grier 2010)

By labeling himself as an Analytical, Babbage was first identifying with a school of European mathematicians, such as Leonhard Euler or Joseph Louis Lagrange, who approached the study of calculus in a certain way. However, Babbage broadened his definition to analysis to include almost any activity that divided work into small pieces, create a symbol for those pieces and manipulated those symbols mechanically. (He named his second computing machine the "Analytical Engine" because it was capable of manipulating mathematical symbols in such a way.) (Grier 2011)

Because of his analytical background and his interest in machinery, Babbage studied the organization of factories and production. The result of this work he published, On the Economy of Machinery and Manufacturers, in 1831. The book combines broad principles of industrial organization with surprisingly detailed

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comments on industrial tasks. He gives principles of using machinery and mixes them with comments on cutting glass and splitting wood. In it, he builds upon Smith's work and moves beyond the division of labor by time, place, object and person to the division of labor by skill.

In considering the division of labor, Babbage realized that the division of labor by skill had more economic impact than the other four forms of divided labor. "That the master manufacturer, by dividing the work to be executed into different processes, each requiring different degrees of skill or of force," he wrote can purchase exactly that precise quantity of both which is necessary for each process"(Babbage 1831) He argued that if you did not divide work by skill, the manufacture would have to hire people who had all the skills necessary for the job. Such individuals, he observed, would be unlikely to perform all skills equally well and would be more expensive than workers who had only a single skill. This observation is generally known now as Babbage Rule. (Braverman 1975)

The Progenitor to Crowdsourcing: Dividing Mental Labor

In the Economy of Machinery and Manufacturers, Babbage applied the ides of divided labor to clerical tasks and calculation, categories of work that he identified as mental labor. It may, he wrote, "appear paradoxical to some of our readers that the division of labour can be applied with equal success to mental as to mechanical operations." He argued that not only was such work governed by the principles of Adam Smith but that showed that it showed that manufacturing was "founded on principles of deeper root than may have been supposed."(Babbage 1831)

At the time, both Great Britain and France did scientific calculation, one of Babbage's forms of mental labor, with methods that were quite similar to modern crowdsourcing. Beginning in 1767, British Nautical Almanac used freelance workers to prepare its annual volume of astronomical tables. These workers were generally teachers or clerics in the British Isles, though at least one worker was the widow of a cleric and the other was a teacher who lived in North America and communicated with the Almanac office through the slow and irregular North Atlantic mails. (Grier 2005)

The workers for the Almanac would get their assignments in much the way that crowd workers would get their assigns from the markets at oDesk or eLance. The director of the Almanac would determine which charts needed to be calculated and describe the nature of the calculations. He offered these calculations to anyone who was qualified and willing to do them. The workers would accept the tasks and do them at their homes. Most used this job to supplement their income. (Grier 2005)

In writing about calculation, Babbage argued that since it was governed by the same economic laws as physical labor, it would be pulled into the same forms of production as had word working or pottery. He noted that economic forces "causes large capitals to be embarked in extensive factories." In a crude way, this argue presages the argument, made 100 years later by Ronald Coase, for the existence of organized companies. "The main reason," argued Coase, "why it is profitable to

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establish a firm would seem to be there is a cost" to making all decisions in the market. (Coase 1937)

Indeed, in 1831, the Nautical Almanac was in the process of moving its production into a single office and eliminating freelance computation. Babbage had been on the committee that had reviewed the Almanac and had recommended the new computing factory model. He also watched as a second computing office, that at the Royal Observatory at Greenwich, also adopted factory models for its calculation. (Grier 2005)

Babbage got many of his ideas about mental labor, the organized processing of information by studying the computing office of the French civil surveying office, or Bureau Cadastre. By any measure, the Bureau Cadastre followed factory precepts. It operated a single computing office in Paris and employed no freelancers. However, it served as a model for later efforts that were much closer to crowdsourcing and it also taught Babbage about the division of labor by skill and how to utilize machinery to minimize costs. (Grier 2005)

The Bureau Cadastre operated a computing office from 1791 to about 1795 under the direction of the engineer, Gaspard de Prony. The Revolutionary French Government had assigned this office the task of creating trigonometric tables for surveying and navigation. In particular, they wanted these tables based not on the standard units that divided a circle into 360° but a new division that divided each quarter circle into 100 grads. (Daston 1994) (Rogel 2010)

De Prony divided the calculations by skill. He created three groups of workers. The first group was a small office of well-trained mathematicians. The Author de Roegel argues that this group may have had about six individuals, including the mathematician Andrien-Marie Legendre. It identified the equations that would be used in the calculation. The second group was less skilled than the first. It took the equations and used them to compute some of the basic values of the trigonometric functions. This group was called calculateurs. The third group was the least skilled. They took the basic values from the calculateurs and interpolated intermediate values between them. De Roegel notes that this group was the largest of the three. It had at least 15 workers and might have had as many as 60. De Prony once claimed that it had 150 workers. (Rogel 2010)

In writing about the Bureau Cadastre, Babbage was primarily interested in the problem of refactorization, of dividing labor and utilizing machines for some of the tasks. The "possibility of performing arithmetical calculations by machinery may appear to non-mathematical readers to be rather too large a postulate," he explained. However he would "remove a small portion of the veil which covers that apparent mystery."(Babbage 1831) He argued that his first computing machine, the Difference Engine could do exactly the kind of interpolation that was done at the Bureau Cadastre. "The ease and precision with which it works leave no room to doubt its success," he added. (Babbage 1831)

The Bureau Cadastre operated for only 3 years before it was disbanded. "The division of labour cannot be successfully practiced unless there exists a great demand for its" products, Babbage noted, "and it requires a large capital to be employed in those arts in which it is used."(Babbage 1831) Indeed, few organizations could afford

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to support any information processing office, much less a scientific computing office. During the rest of the nineteenth century, most of the scientific computing was done on a small scale. A single scientist would do the work, aided by a student, a child, or a spouse. The few large computing organizations, such as the American Nautical Almanac or the Harvard Observatory, tended to build computing factories because they were able to do more work with their resources. They also tended to look closely at how they could substitute machinery for labor. None tried to build a complex computing machine like Babbage's Difference Engine. However, many of them were able to expand their capacity by using small, mass produced adding machines. (Grier 2005)

Resurrection of the Bureau Cadastre as a Crowdsourced Organization

In 1938, the American Government created a computing organization that was based on the model of the Bureau Cadastre and used methods that were much closer to those of modern crowdsourcing. This organization, called the Mathematical Tables Project, followed the outlines of the Bureau Cadastre. It had three divisions. The first were senior mathematicians who identified the calculations. The second was a planning committee who created worksheets to guide the work. The third was group of clerks who completed the worksheets. In general, the members of this last group had limited mathematical skills. They were usually asked only to do addition or subtraction. (Grier 2005)

Unlike the Bureau Cadastre, the Mathematical Tables Project used market mechanisms to manage its workers. It hired senior mathematicians as freelancers to identify the calculations. It used a two-stage market to engage the clerks in the third group. Unlike modern crowdsourcing operations, it was restricted only to a crowd that lived close to its base of operations in New York City. Still, within the limits of the communications technology of the time, it operated much as a complex crowdsourcing company of the twenty first century. (Grier 2005)

At its founding, the Mathematical Tables Project represented a retreat from the practices of its day. Most organizations wanted long term relationships with clerical employees. They wanted the employees to learn more about the organization, gain skill in their job and become more efficient. The most prominent expert on organizing office work in that age was William Henry Leffingwell, whose book, A Textbook of Office Management, was widely read by office directors. In it he argued that office workers needed to be permanent members of the staff. If large numbers of workers were leaving their jobs after a short time, they represented "a serious loss." (Leffingwell 1932)

Leffingwell was a student of Frederick Winslow Taylor, the mechanical engineer who invented the concept of scientific management. Taylor's system involved dividing work into small tasks, analyzing these tasks and setting goals for the workers and using a task market to pay the workers. The workers would be rewarded for

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each task completed. However, Taylor did not want the workers to gain control of production through the task market. He was often critical of factories that used a task market and didn't attempt to set standards for production. In reviewing one factory, he argued that "The workmen together had carefully planned just how fast each job should be done, and they had set a pace for each machine throughout the shop." (Taylor 1911)

Yet 1938 was not the easiest year in which to apply the ideas of scientific management. The United States had been in a depression for 9 years and had recently seen a sharp rise in unemployment. The Administration of Franklin Roosevelt had set the goal of getting jobs for workers. "Our greatest primary task is to put people to work," Roosevelt had explained to the nation. He wanted to find jobs for people even if the work was not always profitable. "The joy, the moral stimulation of work," he added, "no longer must be forgotten in the mad chase of evanescent profits." (Roosevelt 1933)

The Mathematical Tables Project was therefore organized as a work relief effort. It had to be flexible. It had to make use of workers when they were available and be ready to train new workers when they arrived. To do this, it used a two-stage market. It used one market to get workers. That market was run by the Works Progress Administration, the financier of the project. Each day, the project would tell the main Works Progress Administration how many workers it could use and accepted the workers that came from that office. (Grier 2005)

The Project operated a second market within its office. This market was represented by a rack of worksheets. Each worker would take sheets from the rack, complete the calculations and return the sheets to the rack. They had to complete a minimal number of worksheets each day to be paid. (Grier 2005)

Though the project followed the crowdsourcing model, it pushed to refactor labor and move towards a factory model, much as Charles Babbage had observed 100 years before. The leaders pushed to acquire calculating machines and punched card equipment, arguing that these devices made the group more efficient. The manager of the organization, Arnold Lowan, argued that such machinery allowed handicapped workers to do more. It "has been found from actual work records over an extended period of time," explained one report, "that one armed operated using the new Frieden calculator was able to produce 40 % more work an unimpaired worker using a calculator which is not fully automatic." (Grier 2005)

Lowan also reduced the size of the organization and strived to retain workers. He was motivated partially by ambition and partially by rising labor costs. He desperately wanted the organization to be accepted by American scientific institutions. For the first 2 or 3 years of operation, he regularly wrote to university scientists and begged them to give him something to compute. Rarely did he receive a reply much less a problem. Furthermore, the nation's scientific leadership was skeptical of the group. They argued that the unemployed were not prepared to do scientific work and so the Mathematical Tables Project could not be expected to produce valid results. (Grier 2005)

However, by 1941, Lowen felt the pressure of rising labor costs more than desire to build a respectable organization. The preparation for the second world war

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required large numbers of workers and had raised the cost of labor. Lowan, who once could rely on a large pool of inexpensive workers, now had to try to keep every worker he could find. As Leffingwell argued, he tried to keep workers and give them an opportunity to build skill. By the start of the war, he was offering mathematics classes to his workers in order to keep them engaged in the process. (Grier 2005)

Shortly after Pearl Harbor, the group split in two. The Navy took one group and had them prepare navigation charts. The Office of Scientific research and development took the other and had them to general-purpose scientific calculation. This second group was the most active computing organization of the war. Still, the combined size of the two was a small fraction of the original organization. The Navy group had roughly 50 workers while the other group had 25. At its inception, the project had 450 workers. (Grier 2005)

During the war, both parts of the Mathematical Tables Project worked to systematize their operations and move away from a management model that resembled crowdsourcing. The Naval Section of the project moved quickly towards this goal. It produced only one kind of calculation, navigation tables for the new LORAN radio navigation system. The leader of the section, the mathematician Milton Abramowitz, devoted a great deal of time to studying the algorithm that produced the tables. He discovered a way of reusing information and several steps that could be simplified. Finally, as Babbage had done 100 and 10 years before, he explored ways of substituting machine work for human labor. He first introduced adding machines into the process and later, found a way to do a substantial fraction of the calculations with punched card machines. The punched card machines actually used a more complicated algorithm than the hand computation, but it produced results that required substantially less review for errors. (Grier 2005)

The other section of the Mathematical Tables Project also worked to simply operations, remove market management techniques and substitute machines for human labor. As it was a general purpose computing office, it was driven less by a single, repeated calculation than by the need to be able to address many different kinds of problems in a short period of time. The mathematical leader, Gertrude Blanch, found that the project received many requests that simply required too much effort to prepare for the large group of modestly skilled clerks. (Grier 2005)

Initially, Blanch tended to do many of these special jobs herself, spending an extra evening or weekend had her adding machine. However, by the fall of 1942 or the winter of 1943, she received too many requests to be able to handle them herself. As others had before he, she worked to improve the skills of her workers and extend their capacity through adding machines. In this work, she was added by the mathematician Cornelius Lanczos, who had once served as Albert Einstein's research assistant. Blanch and Lanczos ran a series of classes to train the workers. These classes began with the basic properties of arithmetic and ended with college level course on numerical analysis. (Grier 2005)

Even though Blanch moved her office away form crowdsourced management methods during the war, she still occasionally used the methods of crowdsourcing for sensitive or secret calculations. Both the Office of Scientific Research and Development and the U. S. Army regularly asked for computations that it wished to

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keep secret. These calculations included radar tables, bombing plans, shock wave propagations, and, most famously, a serious of calculations for the plutonium bomb being designed at Los Alamitos. (Grier 2005)

The Office of Scientific Research and Development considered the staff of the Mathematical to be a security risk. Many of them came from social groups that the Army considered to be unreliable or had had had dubious associations during the 1930s. Blanch, for example, lived with a sister who recruited for the Communist Party. For these calculations, Blanch would receive the request from mathematicians outside of the project. These requests would have no reference to the physical problem behind the calculation or any hint of the physical units of the various elements. Blanch would convert these requests to worksheets which further obscured the calculations. (Grier 2005)

Other War Time Crowdsourcing Efforts

Though the Mathematical Tables Project moved away from crowdsourcing during the war, other organizations embraced methods for raising funds or producing goods. In some ways, the second world war was a war of amateurs, a war that asked people to undertake roles that they had not done before. Women moved into factories, shop stewards became factory managers, factory managers became entrepreneurs. In this environment, organizations regularly turned to their employees for innovation in much the same way that companies turn to crowds for the same ideas. (Grier 2005)

The methods of crowdsourced innovation in the 1940s were called "suggestion systems" and these processes were symbolized by the suggestion box. Though such systems fell into disfavor during the 1950s, they were a common practice in the 1930s and 1940s. They had been developed during the first world war by the National Cash Register Company and had been promoted during the 1920s by the National Association for Suggestion Systems. Among the organizations that used suggestion systems were Swift Meats, United Airlines, People's gas and Light, Firestone Rubber and Westinghouse. (National Association for Suggestion Systems 1944)

The National Association for Suggestion Systems published books that described how to design and operate such systems. The theory behind these books was quite similar to the theories of open innovation. It posited that the employees of a company had untapped knowledge about the company's products and production methods. It presented ways of soliciting ideas from employees, curating and developing those ideas, testing the ideas in practice and rewarding the ideas. (National Association for Suggestion Systems 1944)

During the war, many, many organizations also used ideas that were similar to the modern idea of crowdfunding. These organizations ranged from the Federal government, which sold low value War Bonds, to local Community Chests, which raised funds for families with soldiers oversees. Of course, the idea of passing the

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hat and raising funds from small contributions is probably as old as the monetary economy itself. However, the process had been developed into a carefully designed system during the 1938s, when the National Foundation for Infantile Paralysis looked for ways of raising large amounts of money for polio research. He developed an idea that became known as the "March of Dimes." (Helfand et al. 2001)

The March of Dimes swept through a social network in much the way that crowdfunding attempts to harness a social network. It restricted contributions to a small amount, ten cents, and began building a social network to gather funds. They started with the supporters of President Roosevelt, who had suffered from this disease, and urged them to collect money from their families and then move to friends and neighbors. The campaign quickly acquired the name "March of Dimes." (Helfand et al. 2001)

Though many organizations used methods that resembled modern crowdsourcing, at least one organized argued that crowdsourcing techniques, especially those techniques that used crowds to gather information, were inferior to more systematic methods. That organization, American Public Opinion, was promoting statistical surveys and random sampling techniques as a means of gathering information. Prior to the mid-1930s, many commercial and government organizations had used crowdsourcing as a means of collecting information. They would distribute penny postcards to the crowd and ask the members of the crowd to send them certain information or pass the card to someone who could. During the first world war, this method had been heavily used by the U. S. Food Administration to gather information on food prices, local crop production, and farm labor. Mass market periodicals used the technique to gather consumer information from their readers. (Robinson 1932)

Many private and governmental organizations continued to use the penny postcards to gather information through the 1940s even though the American Public Opinion Company had decisively demonstrated the values of such methods during the 1936 election. The statistical techniques required expertise that was not commonly found in many organizations. They were also expensive to conduct. By contrast, a penny postcard effort could be managed by a couple of clerks. To promote the new statistical techniques, the U. S. Government published several books and pamphlets on sampling and distributed them widely. (Hansen and Demming 1932)

Crowdsourcing After the War

The end of the war not only ended the conflict it also ended many of the production methods that we compare to crowdsourcing techniques. Writers as diverse as John Kenneth Galbraith, William Whyte and Peter Drucker pointed a society that desired economic stability and feared the return of the depression, just as the recession of 1922 had followed the first world war. However, a few organizations, such as the Mathematical Tables Project, continued to explore crowdsourced methods. The Federal government reunited the two parts of the project into a single office under the management of the National Bureau of Standards. For 3 years, the bureau debated the fate of the organization. Many scientists argued that the new electronic

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computer made the group obsolete. Others, including John von Neumann, argued that the group might be useful for a decade or so. He noted that the leaders knew a great deal about organizing computation and about identifying errors in calculation. (Grier 2005)

In the end, the Bureau shut the Mathematical Tables Project office in New York and transferred about 25 members of the group to a new office in Washington DC. This group joined a new Applied Mathematics Laboratory and served as a general computing group. As all the members of this group were highly skilled in computation, they abandoned their old methods that resembled crowdsourced microtasks.

In 1952, the new Applied Mathematics Office returned to crowdsourced techniques, though in form that differed substantially from their 1930s operations. At the urging of MIT mathematician Philip Davis, the office started to write a new handbook for hand computation. For nearly 5 years, Davis had been arguing that electronic computers would not be readily available to ordinary scientists and engineers for two decades. To bridge this gap, he wanted a handbook that would present the best methods for computation. (Grier 2005)

The veterans of the Mathematical Tables Project created the handbook through a partial crowdsourcing technique. It developed a list of prospective chapters and circulated that list among the former members of the project and people who have been in contact with the group. In a few cases, the editor, Milton Abramowitz, had to pressure a former member to agree to do a chapter. In all, the bulk of the book was written by members of the book. A few chapters were written by individuals who had been part of the Applied Mathematics Laboratory after the war. The book was published in 1964 as the Handbook of Mathematical Functions.

Summary

We should not be surprised that we can find historical antecedents to crowdsourcing. If anything, we should be surprised if we could not find them. Afterall, the current concepts of employment have been shaped by things such as the vertically structured corporation, mass production, mass distribution and mass consumption, all of which have relatively short histories. (Chandler 1977) (Benniger 1986) Even at the start of the industrial age, we can find examples of self-organized crowd labor that resembles the self-organized crowds of the Red Balloon Challenge. (Montgomery 1987) (Tang et al. 2011)

In reviewing the history of organizations that use crowdsourcing techniques, we can see patters that reflect the cost of labor and tolerance of risk. In general, organizations are more interested in using these techniques when the cost of labor is low and economic conditions make it risky to create a large permanent organization. These same organizations move start building more permanent organizations when the cost of labor starts to increase and when they start to feel that they have invested in their workers and don't wish to lose them.

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Finally, we can also see that many of the concepts of crowdsourcing were discussed by Charles Babbage in his analysis of scientific computation and mental labor. Babbage foresee the modern internet any more than he foresaw the modern computer. His second computing machine, the Analytical Engine, is closer to a programmable calculator than a modern computer. Still he saw that any data processing activity could be divided into small tasks, that these tasks could be priced according to the skill required for each task, and that they could be offered to workers in a way that got the right skills into the right part of that activity. Babbage is one of the key forbearers of computation. He is also a forbearer of crowdsourcing as well.

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Ant Colonies as a Model of Human Computation

Melanie Moses, Tatiana Flanagan, Kenneth Letendre, and Matthew Fricke

Organisms process information in order to survive and reproduce. Biological computation is often distributed across multiple interacting agents, and is more adaptive, robust and scalable than traditional computation that relies on a central processing unit to schedule and allocate resources. In this chapter we highlight key features of computation in living systems, particularly focusing on the distributed computation of ant colonies as a model for collaborative human computation.

Natural computation is necessarily robust because sensory inputs are noisy and error prone, and appropriate behavioral responses are contingent on dynamic and unpredictable environments. For example, plant and animal cells extract information from the dynamic chemical soup in which they exist and convert that information into actions. Cells transmit information from the cell membrane via signal transduction pathways throughout the cell. These signals interact with molecules and structures built by the cell according to instructions encoded in DNA. Cellular computation is distributed across a Byzantine set of chemical reactions that are robust to individual component failures (Bray 1990, 1995). There is no central controller in the cell; instead myriad processes act in parallel and the interaction among processes give rise to behavior.

The immune system is another information storage and computational system in multi-cellular animals. The cells that comprise the immune system collectively distinguish self from other and remember previously encountered pathogens (Von Boehmer 1990). Immune cells respond only to local information but collectively mount a coherent global response to infection. The tolerance of T cells to "self" proteins exemplifies this process: T cells that bind to an animal's own healthy cells are eliminated in the thymus, thus all remaining T cells can safely attack cells to which they bind without checking any central authority. Immune cells release and respond to chemical signals such as chemokines that direct cell movement in space

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and cytokines that regulate cellular activity (Rossi and Zlotnik 2000). Cells move and react based on random sampling combined with positive and negative reinforcement from chemical intermediaries, enabling the immune system to self-regulate without central control (Moses and Banerjee 2011).

The brain is a more obvious computing machine than a cell or an immune system, but similar computation occurs through the interaction of billions of individual neurons each responding to thousands of inputs using a redundant and distributed network of neural pathways. Animals are computing systems that integrate immune systems, brains, sensory input and other organ systems, each made up of individual cells carrying out local tasks.

Superorganisms, such as ants, and bees are groups of individual organisms in which natural selection acts primarily on a colony's collective behavior. The computational capabilities of colonies emerge from interactions among individuals (Greene and Gordon 2003). These interactions range from direct antennal contacts between ants to communication via stigmergy, such as laying chemical pheromones in the environment where they are sensed, responded to, and sometimes reinforced by other ants. Colonies demonstrate how cooperative computation can be organized among autonomous agents, each individually capable of its own local computation.

Each of these biological systems—cells, brains, and ant colonies have inspired successful computational algorithms and heuristics. The behavior of cells inspired the development of cellular automata (Von Neumann and Burks 1966) and more recently, membrane computing (Berry and Boudol 1992; Cardelli 2005). Neural networks, first developed as models of the neuron, were quickly incorporated into the first computers (McCulloch and Pitts 1943), and have since become ubiquitous tools for solving classification problems which require generalization and plasticity. Artificial immune systems are algorithms and architectures that mimic biological immune systems in order to secure computers (Bersini and Varela 1991; Forrest and Perelson 1991). The recognition that evolution itself is a powerful computational process led to the field of Genetic Algorithms (Holland 1975; Mitchell 2006; Schwefel 1965), which have taken a central place along with neural networks to solve a vast array of optimization problems. The collective computational abilities of ants inspired Ant Colony Optimization (ACO) algorithms that mimic ant chemical communication via pheromones to focus computational resources on successful partial problem solutions (Dorigo 1992). ACO have been successful in a wide variety of problem domains, particularly in scheduling and routing tasks (Dorigo and Stützle 2010). ACO are also a key component of the field of Swarm Intelligence, which examines how collective computation can emerge from interactions among local agents, for example in swarm robotics (Hecker et al. 2012; Brambilla et al. 2012).

A recent response to the need for scalable, adaptable and robust computing that more closely mimics natural systems is the Movable Feast Machine (MFM, Ackley et al. 2013). A MFM is composed of relatively simple computational modules containing a processor, memory, and input/output ports; the computational power of the MFM comes from spatial interactions among the components that maintain a sort of computational homeostasis that is resilient to disturbance from hardware failure or malicious attack. In much the same way that multiple ants in a colony contribute to

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a collective goal while minimizing the propagation of individual mistakes, the MFM combines multiple processors into a distributed scalable system in which the computation of the system is more robust than that of its individual components.

In this chapter we transcend specific classes of algorithms like ACO and explore ant colonies more generally as complex systems capable of computation. We describe the manner in which ants, seen as simple agents, are able to use local information and behavior to produce colony wide behavior that is robust and adaptive. Ant colonies are particularly suitable models for distributed human computation because they demonstrate how individuals can collaborate in order to perform qualitatively different computations from those any individual agent could perform in isolation. This feature of ant colonies has led them to become extraordinarily successful foragers, dominating ecosystems across the globe for tens of millions of years. While there are key differences between ant colonies and collections of human agents, the nascent field of human computation can learn from the myriad strategies that ants have evolved for successful cooperation.

Colony Computation

Colony computation is distributed, adaptive, robust and scalable to large numbers of ants. Colony computation includes, for example, processes of collective decision-making (Franks et al. 2006; Marshall et al. 2009), task allocation (Gordon 2002; Pacala et al. 1996), and regulation of activities such as selecting new nest sites and foraging (Beverly et al. 2009; Franks and Deneubourg 1997; Gordon 2010; Mailleux et al. 2003). Here we focus on foraging behavior as a collective process in which individual ants react to local environmental conditions and information, including information produced by other ants, without central control (Bonabeau et al. 1999, 1997; Camazine et al. 2001).

Foraging ants exploit spatial information without building maps, balance exploration and exploitation without explicit planning or centrally directed task assignments, and leverage noise and stochasticity to improve search. Communication among ants is embodied in physical signals that are inherently local, decentralized, and used only when needed. Foraging is achieved without centralized coordination. Ant behavioral responses to local information regulate colony behavior; thus, the collective behavior of the colony emerges from local interactions (Gordon 2010; Pinter-Wollman et al. 2011; Prabhakar et al. 2012). The resulting colony dynamics are adaptive, robust and scalable, similar to other complex distributed biological systems such as immune systems (Moses and Banerjee 2011).

Colony computation is adaptive: Ant colonies adapt their foraging strategy as they sense features of the surrounding environment. For example, foraging behaviors change in response to incoming cues that reduce uncertainty about the location and availability of food. Pheromones, direct physical contact between ants, and food sharing are all examples of interactions that communicate information about food

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locations. Cues can be conveyed to the colony with the discovery of each food source, and the colony can respond with a strategy appropriate to the average availability and distribution of food in that species' environment (Flanagan et al. 2011).

Ants adjust collective and individual behaviors in response to the availability and distribution of food. Colonies increase activity when resources are more abundant (Crist and MacMahon 1992; Davidson 1997). Group foragers tend to focus on high-density resources, with distinct trails forming to rich resource patches (Davidson 1977), which become increasingly longer with decreasing resource density in the environment (Bernstein, 1975), providing an efficient search strategy for dispersed resources and greater energetic return for the colony. Ants can communicate food locations by laying chemical pheromone trails that other ants follow and reinforce if they successfully lead to food (Wilson 1965). Pheromones exemplify how colonies incorporate the physical environment (in this case, the ground) and stochastic interactions into their computation. In this system, the chance encounters of foragers with physically embodied pheromone signals balances exploration with exploitation: ants that happen not to encounter pheromones will explore for other resource locations, while ants that follow pheromones reinforce exploitation of known resources. Trails allow the colony to adjust the number of foragers to form stronger trails towards more abundant food (Detrain et al. 1999). The Argentine ant *Iridomyrmex humilis* makes extensive use of pheromone trails to recruit other ants to newly discovered food sources (Aron et al. 1989). New World leafcutter ants (*Atta* and *Acromyrmex* spp.) create large visible trunk trails in order to harvest massive quantities of leaves clumped on individual trees (Wilson and Osborne 1971).

Pheromones are not the only form of communication. For example, in *Pogonomyrmex* seed harvesters, foragers are stimulated to leave the nest by the return of successful foragers: the probability of beginning a new foraging trip increases as the encounter rate with foragers returning with seeds increases. This positive feedback mediated by the simple encounter rate among ants enables the colony to increase foraging activity in response to currently available food (Schafer et al. 2006).

Colony computation is robust: Workers of ant colonies face a variety of predators, parasites (Whitford and Bryant 1979) and adverse environmental conditions that impose mortality risks (Whitford and Ettershank 1975). Sometimes, whole-colony disturbances can disrupt colony tasks (Backen et al. 2000). Two particular features of colonies lead to robustness: the absence of central control or communication prevents single points of failure, and the ability of many individuals to perform the same task provides the flexibility necessary to tolerate disturbances and loss of colony members. While the redundancy required to respond to changing needs may appear inefficient, when integrated over long time periods and dynamic and unpredictable environments, such robustness may actually optimize performance of tasks such as food collection. For example, in a redundant work-force, individual ants are able to take risks because similar ants are available to compensate for mistakes.

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Additionally, small individual differences among ants may cause slight variations in foraging behaviours which may be useful in unpredictable and dynamic environments. Successful behaviours can be reinforced through recruitment.

While some colonies have a few morphologically distinct castes, most ants are arranged in much more flexible task groups, often with individuals cycling through different tasks as they age (Gordon 1999). Ants respond to changes in demand for a particular task by reacting to local cues and switching to a task when that task is completed at a slower rate compared to other tasks. For example, in *Leptothorax* ant colonies, after a disturbance, each individual reacts independently, returning quickly to its work zone and resuming the disrupted task (Backen et al. 2000). This decentralized task allocation provides the colony flexibility and responsiveness to internal and external changes without reliance on any centralized authority (Bourke and Franks 1995). Thus, robustness arises from this independent action of individuals combined with the redundancy of individuals that can tackle a task concurrently or easily switch tasks. Similar to the "c-factor" which predicts success at collective tasks in groups with high social sensitivity and equity (Woolley et al. 2010), the ability of ants to simultaneously communicate effectively and substitute the actions of one ant for another may contribute to colony success.

Colony computation is scalable: Colonies range in size from dozens to millions of ants (Beckers et al. 1989). Distributed communication and lack of central control lead to colony computation being highly scalable. When communication and actions are executed locally, each ant can respond quickly regardless of the size of the colony.

However, foraging presents a particular challenge to scalability. Central place foraging may incur substantial travel costs for each ant when the foraging area is large. As ants transport resources between a central place and the space of the territory, the work a colony must do to acquire food increases faster than the number of foragers (Moses 2005). Thus, colonies experience diminishing returns as the individual cost of transport increases with colony size.

To achieve efficiency at scale, each forager can react to local cues and interact within a small local range with others, forming large information-sharing networks linked by individual interactions and pheromone trails (Holldobler and Wilson 1990). These structures particularly improve foraging efficiency in large colonies that have more workers to acquire information to make effective group decisions and mobilize a large, fast response (Anderson and McShea 2001; Aron et al. 1989).

Polydomous ant colonies have evolved multiple interconnected nests which decentralize foraging in space and increase scalability. In *Myrmicaria opaciventris* (Kenne and Dejean 1999) and the invasive Argentine ant, Linepith the exploitation of a foraging area is transformed into an additional nest site, enabling reduction of the transport cost in colonies with a large number of foragers (Debout et al. 2007). The wide-ranging trail and dispersed nest system of the polydomous Argentine ant includes dynamic, flexible foraging trails (Fig. 1a) that grow and contract seasonally (Heller and Gordon 2006) and in synchrony with the availability of food sources. Dynamic local recruitment of ants from trails rather than from more distant nests further reduces individual travel costs (Fig. 1b) (Flanagan et al. 2013).

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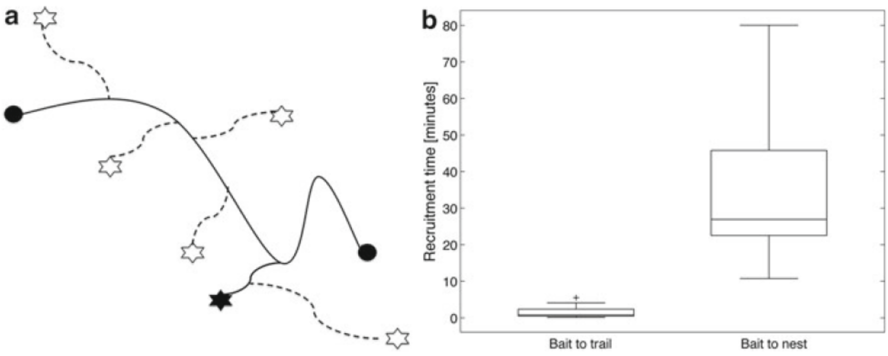

Fig. 1 (**a**) Argentine ants form dynamic trail and nest systems that grow and contract according to availability of food sources. Trails to ephemeral food sources are short-lived, disappearing once the food is no longer available. Trails to stable food sources become more permanent and may give way to other branches. Circles are nests, solid lines are permanent trails to permanent food sources (*blue stars*). Dotted lines are transient trails to ephemeral food sources (*orange stars*) (**b**) the box-plot shows round trip transport time from bait to the trail versus the round trip time from the bait to the closest nest. Mean travel time is significantly reduced ($p < 0.001$) by recruiting from the nearest trail instead of the nest (Data from Flanagan et al. 2013)

The Argentine ant strategy of recruitment from trails suggests a solution to a common engineering problem, that of collecting or distributing resources in "the last mile" where infrastructure networks connect to individual consumers. In biological and engineered networks, the dynamics in the last mile can set the pace of the entire system (Banavar et al. 2010). The last mile presents a challenge, because if a network delivers or collects resources in a large area, the majority of the network wires may be in the many short-distance low-capacity links that fill the last mile.

Wireless networks make coverage of the last mile less difficult. Just as cell phone towers maintain links only when a phone is active, the ephemeral recruitment trails of invasive Argentine ants appear and disappear as needed, allowing ants to gather dispersed resources without the infrastructure costs of permanant trails. Ants that discover new food, and go to the trail to communicate that discovery to nearby ants, act as relays that efficiently route ants to ephemeral food. The network exists only when it is needed—when the resource is exhausted, the network can disappear so that effort can be invested elsewhere. The ability of Argentine ants to cover the last mile with ephemeral trails is yet another example of a solution to a search and communication problem evolved by ants that mirror or inspire approaches used by engineers (Dorigo et al. 2006; Prabhakar et al. 2012).

There are tradeoffs inherent in the adaptive, robust and scalable computing strategies used by ants. For example, ant colonies balance the costs and benefits of private individual information versus communicated social information. The location of food may be stored in individual memory (Czaczkes et al. 2011) or communicated via pheromone trails (MacGregor 1947; Wilson and Osborne 1971). An individual ant can forage efficiently by making repeated trips from the nest to a

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known foraging site, without recruiting other foragers to the effort (Letendre and Moses 2013), a behavior known as site fidelity (Holldobler 1976). If a forager discovers a particularly good foraging site, whole-colony foraging success may be improved by communicating the location to its nestmates. However, too much communication can reduce foraging success if too many foragers are recruited to a site; that overshoot leaves foragers searching an area depleted of seeds (Wilson 1962). Thus, ants must balance the use of private and social information in their foraging (Grüter et al. 2011; Letendre and Moses 2013).

In order to gain insights into how ants make this trade-off, we have used genetic algorithms (GAs) to find the optimal balance of site fidelity and recruitment to maximize seed collection rates by colonies of simulated ants (Flanagan et al. 2011, 2012; Letendre and Moses 2013). We select for solutions that maximize food collection at the level of the colony, even though simulated ants can only perceive and communicate locally. The GA selects individual behaviors that are adaptive in obtaining a whole colony solution.

Ants make decisions based on local knowledge of a foraging site: when to recruit other ants to the site; when to continue foraging at the known site; or when to abandon a known site and instead follow recruitment trails to a new site. Because an individual ant knows food availability on only a small portion of the colony's territory, it cannot know with certainty if other ants have discovered better foraging sites than its own. The group level selection in our model results in ants with behavioral responses to local conditions which produce, on average, optimal colony-level responses to a particular food distribution, and the repeated interaction of the ants and repeated sampling of the environment tends to overcome individual errors in decision-making. In colonies evolved by GAs, ants recruit to sites where the availability of food outweighs the problem of overshoot and ants continue to forage at sites until the availability of food is reduced to the point that, on average, it would be more beneficial to follow a pheromone trail to a new site. We hypothesize that natural selection acts similarly, balancing an individual's reliance on its own computation (its own local sensory information or memory) and communicated information (by pheromones, interaction rates or other forms of communication). Thus, each individual's behavior improves collective function on average for that species and its particular foraging ecology.

We have illustrated the potential benefits of individual memory and social information in simulations in which ants may use site fidelity or recruitment alone, or both together, and compared their performance at food collection to models in which ant use no information and search at random (Letendre and Moses 2013). We found that in an environment which food is power-law distributed spatially—a random scattering of seeds, many small piles, and a few large, dense piles of seeds—site fidelity and recruitment increase foraging rate by 35 % and 19 % respectively (Fig. 2). For these simulated ants, individual memory appears to be generally of more benefit than social information when the two are isolated. However, combining the two forms of information further increases foraging rate to 48 % over colonies of ants that use no information. Differences in foraging success are even more pronounced when ants are foraging on foods more patchily distributed in the environment.

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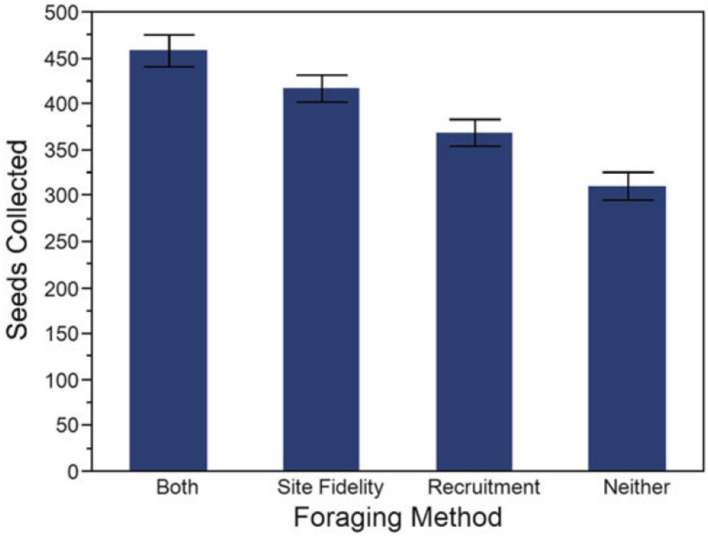

Fig. 2 Foraging success of simulated ants selected by a genetic algorithm to maximize collective foraging success. Colonies of 100 ants forage for power-law distributed seeds using site fidelity, recruitment, both together, or neither, for 10,000 time steps (Letendre and Moses 2013, in press)

Our analysis illustrates a synergy between private and social information. This synergy is especially remarkable in light of the fact that after the optimal balance is struck by the GA between site fidelity and recruitment, 98 % of foraging trips begin with site fidelity compared with only 2 % that begin by following a recruitment trail to a foraging site. The small number of trips that begin following a recruitment trail provide an out-sized benefit by bringing ants to new foraging sites where thereafter they can return to the site using individual memory. The two behaviors are also synergistic in the sense that ants foraging with site fidelity are more successful if they are foraging at a high quality patch to which they have previously been recruited. Additionally, pheromone trails are more useful when they can be limited to very high quality sites because seeds from smaller patches can be collected using site fidelity (Fig. 3). Thus site fidelity can allow recruitment to work more effectively and vice versa.

The combination of individual memory and local computation with communication expands the behavioral repertoire of responses to varying quality of foraging sites. Ants can use site fidelity to effectively collect seeds from small patches and pheromones to collect seeds from large patches. Optimization schemes might similarly be applied in human computation to balance the use of communication versus independent action.

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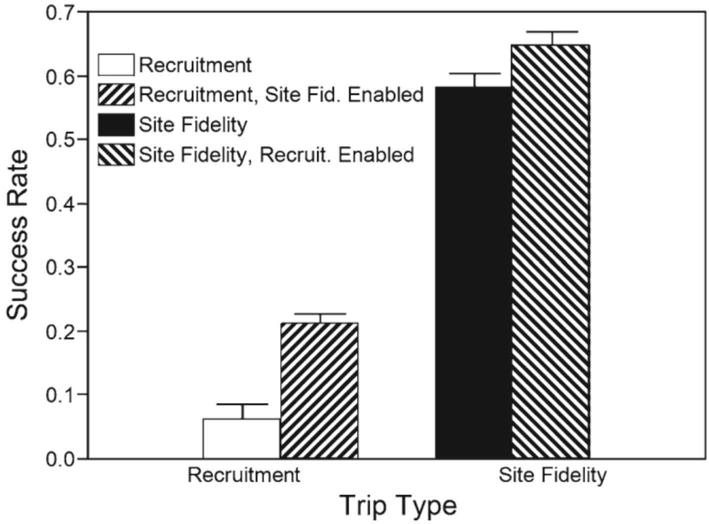

Fig. 3 Frequency that simulated ants using recruitment successfully find a seed at the site to which they have been recruited, and frequency that ants using site fidelity successfully find a seed at a site to which they have returned based on individual memory. The addition of site fidelity to recruitment improves the success rate of recruitment trips; and the addition of recruitment to site fidelity improves the success rate of trips based on site fidelity

Conclusions

The adaptive, robust and scalable computation achieved by ant colonies serves as a model for human computation. The features of social computing in ants have been tuned by natural selection for millions of years to accomplish a wide variety of tasks in a wide variety of environments. Social computing in ants demonstrates that individual behaviors can be selected to maximize collective performance, even when the individuals are unaware of the global goal. Ants act locally, but colonies act globally.

Ant colonies offer several suggestions for how human computation can strive for more than connecting many humans together to gain additive benefit from each human. Ultimately, as in the emergent computation of ant colonies, the sum of human computation should be greater than the individual contributions of each individual. Ants demonstrate the feasibility of collective coherent behavior, even when individuals have only a narrow local perspective. By tuning the rules of interaction, individual behaviors can be rewarded to maximize collective benefit.

It is worth contrasting colony computation with market economies, another complex system in which collective function emerges from interactions among individual agents. While economies and colonies are collective entities whose properties emerge from the interactions of individual agents, colonies largely avoid a pitfall of market economies—the tragedy of the commons in which individuals acting in their own short term best interests deplete shared resources, diminishing the long term interests of the group. While ants in a colony and humans in an economy both

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respond to locally perceived information, human agents in an economy are rewarded based on their own self-interest; in contrast, ants are rewarded based on collective colony interests. Colonies demonstrate how interaction rules can be designed to maximize collective performance rather than individual performance, even when individuals respond only to local information.

The mechanisms by which cooperation emerges in colonies are in some sense unique to the particular physiology of ants. Pheromone communication is useful for animals with highly sensitive smell; ants may react to encounter rates with other ants simply because they are incapable of integrating more complex information. Humans are obviously capable of vastly more sophisticated computation, learning and innovation. Technology allows humans to communicate at any distance. Further, humans can, potentially, choose among numerous biological behaviors to imitate and adapt to their own needs.

Regardless of whether the actual mechanisms for cooperation are the same, successful cooperation in both systems may rest on similar principles. The cooperative behaviors of ants reflect not just the particular physiology of these insects, but also more general principles for cooperative computation that form a foundation for human computation. Like ant colonies, human computational systems should:

- Balance reliance on local verses communicated information
- Decide when successful individuals should guide others and when individuals should explore independently
- Trade-off an individual's attention to a task with the cost of switching to new tasks
- Reinforce good solutions while being robust to local errors

The proper balance of these tradeoffs in individuals results in a synergy at the collective level that balances exploitation of what is already known with exploration for novel solutions. In ants, natural selection has developed an incentive structure that rewards individuals who balance this tradeoff to maximize contributions to global rather than individual goals. Human computational systems will have to engineer incentives to individuals to create the right balance of behaviors for collective computational goals.

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Parallels in Neural and Human Communication Networks

L.J. Larson-Prior

Introduction

This chapter seeks to explore functional characteristics held in common by neurons in the brain and humans in society. A better understanding of the commonalities between brain network computation and human social network function may provide a framework for better understanding the potential for human computation as an emergent behavior. Establishing a mechanism by which differences and similarities in the computational potential of brain and human social networks can be evaluated could provide a basis by which human computation may be operationalized.

Natural systems are complex and dynamic, characteristics that make accurate prediction of their behaviors over time difficult if not impossible. This property is held in common by both physical systems such as the weather and the movement of the earth's crust and biological systems from genetics to ecosystems. Further, these are adaptive systems that have evolved over time to optimize their ability to survive in the face of changing environmental conditions at a range of time scales.

Complex systems are distinguished from complicated systems not on the basis of the number of constituent elements but on the potential to predict system output based upon an understanding of behavior of each element and its position in the system. The requisite characteristic of a complex system is the presence a large number of interacting non-linear elements, be they neurons or humans. The relevant property of complex systems for our purposes here is that they exhibit emergent properties; that is, macroscopic behaviors emerge from the interaction of constituent elements rather than being dictated by some controlling source (Chialvo 2010).

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A hallmark of complex dynamic systems is the presence of abrupt transitions from one physical or behavioral state to another that are termed phase transitions. Examples of such behavior include such everyday occurrences as the transition of water from a liquid to a solid state, or of liquid water to a gas when boiled. Such transitions also characterize biological systems with a common state transition seen, for example, in the alternations between wake and sleep.

A final property common to complex dynamic systems is their organization into interlinked networks. Systems are, by definition, composed of interconnected elements or components that act together to process a set of inputs and produce some behavioral output. Network theory provides a powerful tool by which to describe and analyze the interactions of complex and dynamic systems and has been used in the analysis of brain (Bassett and Bullmore 2006; He et al. 2007), human social (Brown et al. 2007; Gulati et al. 2012) and technical (Barabási et al. 2000; Wang and Chen 2003) systems. Further, network theory offers a common framework within which to understand both the similarities and differences in the computational potential of both neural and human communication systems that is the goal of this chapter.

This chapter will provide overviews of both neural and human social system composition and communication together with the network theory view of their global operations as complex, non-linear dynamic systems. Within that framework we will then move to commonalities in the processing mechanisms of both systems, followed by a short discussion of their differences. A more speculative section concerning the potential for human computation will finalize the chapter.

The Brain as a Complex Dynamic System

The brain is a complex adaptive system that controls organismal behavior to environmental stimuli. Accurate assessment of the context in which a behavioral response will be generated is essential to successful performance and, in many instances, to organismal survival. To achieve appropriate responses to environmental stimuli, the brain must be both sufficiently stable as to estimate the consequences of a response, and sufficiently flexible to respond to completely novel or unexpected stimuli.

The brain is composed of a large set of interacting complex cellular elements, the majority of which fall into the two categories of neurons and glia. Brain processing of both external and internal environmental stimuli involves a complex and incompletely characterized set of interactions between these cellular elements and their extracellular milieu. That said, as the neuronal elements generate the system output structure, the vast majority of studies have focused on the neuron as a central processing element of the brain and it will be on this element that we also will focus.

Neurons, and as is becoming increasingly clear, the glial elements with which they interact, communicate both individually and within circuits that enable dynamic aggregation of processing-specific populations. The system is hierarchical in the sense that circuits themselves interact to form increasingly complex circuits, leading to the identification of processing modules with distinctly different processing parameters (Felleman and Van Essen 1991; Meunier et al. 2010; Zhou et al. 2006).

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An example of one such distinct hierarchical module is the retina of the eye, a complex and hierarchical network of interacting elements that receives light from the external environment, processes that input to provide information on both pattern and color in the external environment and transmits that highly processed information to multiple different circuits in the brain to not only enable the organism to "see" the external world, but also to inform other brain circuits as to the level of light in the external world as a separate input.

Human Social Organization Is a Complex Dynamic System

Human social systems are also adaptive, complex dynamic systems. Human social organization, like that of other social organisms, provides the system as a whole with an adaptive capacity that improves survival and viability. Social systems provide a stable organization in which each individual can operate with established rules by which flexible, adaptive responses may occur. Moreover, social systems undergo phase transitions at both local and global scales, from abrupt shifts in organizational leadership to political or social revolutions that dramatically reorder the social hierarchy (Garmestani et al. 2009; Holling 2001; Wilkinson 2002).

Individual humans are the basic processing element of human social systems. Each individual is unique and complex, and highly connected to other individuals in the society. Social organization begins with connections between individuals (Davidsen et al. 2002) which networks are then embedded in larger network(s). Communication in its multiple forms provides individual members of a society with information required to update experiential data used in decision-making and the guidance of appropriate responses to environmental stimuli.

Human social organization is hierarchical, and each individual is embedded in a complex network that includes family, friends, professional associates and acquaintances (for further discussion, see Analysis Section, this volume). This intricate extended network is clearly seen in the use of social networking sites such as Facebook, Twitter and LinkedIn, where individuals form communication links to others based on personal or professional affiliations. Such linkages extend beyond the individual through organizational behaviors and organizations, and at larger-scale to the behavior of the polity whether local, national, inter-national, or global.

Neural Communication Structures

Although neuronal morphology varies greatly, a characteristic structure can be defined that informs our understanding of the processing capabilities of single brain elements. Neurons are composed of a cell body, the soma, from which extend two different types of processes: the dendrites with are electrically conductive but historically considered passive, and the axon which actively transmits electrical signals. Classically, the dendrites are receptive cellular processes that act to pass

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information to the cell soma, which acts as the cellular processing element. While recent data points to dendritic processing capability (Spruston 2008) information flow to the soma remains fundamentally characteristic. The soma has a highly complex internal structure that provides substrates for information processing, plastic remodeling of cellular morphology and molecular biology, and health maintenance, which can be considered the complex internal structure of the basic brain processing element and not discussed further. From the soma, information is transmitted to other brain cellular elements via the axon. The receptive elements of the neuron are the receptors, which are proteins embedded in, and capable of movement within, the neuronal membrane. Receptors are found predominantly on dendritic membranes, but also exist on the soma.

The neuron is an electrically excitable element, with electrical current generated by the passage of ions across the cell membrane. As noted above, information is transferred between elements via specialized protein complexes known as receptors. The classical neuronal receptors are activated by chemicals synthesized in the neural soma and released based on the voltage potential of the somal membrane, providing the electro-chemical communication system of the brain. As these chemicals and their receptors are found in the brain they are termed neurotransmitters and neurotransmitter receptors. A large number of neurotransmitters exist, most of which bind to specific receptor proteins, acting to change the protein complex conformation and either open ionic channels through the cell membrane or initiate complex intracellular biochemical cascades to affect behavioral changes in the receiving cell. The process of electro-chemical neurotransmission occurs at a specialized region of contact between two cells known as the synaptic cleft. The synaptic cleft is an area of directed cell-to-cell communication, i.e., information is passed from one cell (the presynaptic cell) to another (the postsynaptic cell) unidirectionally. However, there may be more than one synaptic cleft present between two cells, providing for bidirectional information transfer. The presynaptic element is specialized for the release of neurotransmitter into the synaptic cleft. Once released into the synaptic cleft, neurotransmitters diffuse passively across this narrow gap between cell membranes (~ 20 nm). The postsynaptic cell membrane is rich in neurotransmitter receptors capable of binding the released neurochemical. Termination of signaling is accomplished by several mechanisms including reuptake into the presynaptic cell, diffusion out of the synaptic cleft, or enzymatic degradation, creating rapid, point-to-point communication.

While neurochemical communication is rapid, electrical synapses communicate between cells almost instantaneously. Signaling in this type of synaptic contact takes place through specialized transmembrane proteins called connexins that directly couple the presynaptic and postsynaptic membranes, allowing for rapid exchange of ions and metabolites between cells (Nagy et al. 2004; Scemes et al. 2007). This type of cellular communication mechanism has been found to link neuronal and glial elements (Nagy et al. 2004), to provide synchronized activity in glial elements (Theis and Giaume 2012), and to be important in state transitions in the brain (Haas and Landisman 2012).

In addition to rapid, point-to-point communication, less compartmentalized forms of communication are demonstrated by extrasynaptic (volumetric) release of neurotransmitters that act via receptor complexes outside of the synaptic cleft

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(Vizi et al. 2010). Such interactions may occur through activation of peri-synaptic receptors that lie outside of the synaptic cleft but spatially close to it (Oláh et al. 2009; Vizi et al. 2010), or via distant receptors (Fuxe et al. 2013). This communication channel is slower than the point-to-point mechanisms described above (seconds-minutes) and takes place over distances as great as 1 mm from the release site. Thus, the effector region of this type of communication is sufficient to modulate circuit behaviors in a manner analogous to that described in invertebrate systems (DeLong and Nusbaum 2010).

The cellular elements of the brain communicate on different time scales using a wide variety of neurotransmitters whose effects are magnified by their interaction at a large number of receptors with different structures and postsynaptic actions. The fundamental processing unit of the brain is the neural circuit—aggregates of cellular elements and their synaptic and extra-synaptic contacts. Such circuits are formed at multiple levels of complexity, but fundamentally form dense inter-circuit connections with a smaller number of connections to other circuits with which they communicate resulting in the hierarchical architecture noted above for neural systems. To characterize a neural circuit fully would include a full description of the circuit wiring diagram and the neural elements embedded within that structural web, a full understanding of the neurochemical systems by which information was transferred and the time-frame on which such interactions depended together with a comprehensive description of the input–output function of that circuit under the recognition that its behavior is highly likely to be non-linear. Thus, a full description of even a 'simple' neural circuit has not yet been achieved; although a number of models and research studies have pointed to the complex behaviors such circuits are capable of producing (Ahrens et al. 2013; Guertin 2012; Kaneko 2013).

The hierarchical structure of the brain leads us beyond the 'simple' neural circuit, to the complex of circuits that together form the large-scale networks described using neuroimaging methods such as functional magnetic resonance (fMRI) and positron emission tomography (Barch et al. 2000; Dosenbach et al. 2007; Just et al. 2007). Using these methods provides a global view of brain connections during behavior in which interactions encompassing large brain areas connected over long distances can be linked to cognitive behaviors such as learning, memory and attention. Recently, a new area of research into large-scale brain connectivity has been developed based upon imaging of active brain circuitry when the subject is not performing any task, a condition termed 'the resting state' (Biswal et al. 1995; Cohen et al. 2008; Fox et al. 2005; Mennes et al. 2010). The linkage of brain structural connectivity to the functional organization definable during the resting state provides a new window on the organization and function of the brain (Deco et al. 2013).

Human Social Communication

Human communication structures exist at multiple scales, from small groups where contact is frequent, to increasingly distributed interactions where contact is less frequent. Humans transmit information in the form of both oral interactions and via

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the more permanent and globally accessible forms of written communication. Particularly in oral communication, transmitted information content is often modulated by emotional content or non-verbal communication in the form of body-language cues. While visual modulatory cues are not present in written communication, they are often inferred by the reader.

Human social groups cluster at multiple levels, with small groups (cliques, clans, tribes, etc.) having high degrees of internal communication but little communication with other groups (Bryden et al. 2011), an organization termed community structure (Girven and Newman 2002). This organization, described for many aspects of human social interactions, imparts a modular structure to the large-scale network in which communities are richly interconnected locally, but only sparsely connected to other communities in the global networks (Gulati et al. 2012).

Studies examining social network behavior in organizations note that highly local and isolated networks tend toward a homogeneous knowledge and decision base, making it desirable to seek outside contact to drive creativity and innovation (Gulati et al. 2012). The current emphasis on knowledge as a commodity in modern society has led to an increased interest in better understanding the means by which knowledge is disseminated in human social networks (Dupouët and Yıldızoğlu 2006; Morone and Taylor 2004). Human actors can accumulate knowledge by individual learning or through processes of interactive learning, processes that can be carried out both under formal learning conditions such as educational institutions or under informal conditions. An interesting result of simulation studies suggests that widely divergent levels of knowledge within a network tends to lead to a gap in knowledge dissemination, leading to community divisions into a highly knowledgeable, a group that is attaining greater knowledge at a slower rate, and a marginalized group that could be considered ignorant (Morone and Taylor 2004). Moreover, this division does not arise from community structure per se, as communities in which knowledge levels are not highly variable tend to disseminate knowledge efficiently and more equitably (Morone and Taylor 2004).

A sea change in human communication mechanisms was driven by the global introduction of computer-enhanced methods such as email, communication platforms such as Facebook and Twitter, and the interactive informational 'bloggersphere'. An important feature of social communication networks is the interrelationships between them—such that the network of friends, colleagues, and trade-partners influence responses of any individual agent to all networks to which that agent belongs (Szell et al. 2010). While social media can be seen to provide an unprecedented mechanism for the global exchange of knowledge, information, and opinion, to fully comprehend its reach requires a much fuller understanding of these complex inter-relationships.

As is true of the brain, the hierarchical and dynamic properties of human social—and, by extension, economical, technological and political—interactions lead to unpredictable emergent behaviors at multiple levels. Network theory provides a method by which such complexities may be evaluated in both space and time.

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Network Theory Links Neural and Social Communication Systems

We have seen that the brain is a complex dynamic system (Amaral et al. 2004) consisting of on the order of 10^{11} neurons and 10^{15} synaptic connections (Sporns et al. 2005). In common with other complex dynamic systems, the brain exhibits critical dynamics (Chialvo 2010; Poil et al. 2008) and scale-free behavior (as explained below). Human social systems are also complex dynamic systems, with a global population of approximately 7×10^9 human beings according to the US Census Bureau (www.census.gov).

Complex systems exhibit non-random linkages over multiple temporal and spatial scales, a relationship captured by the popular 'six degrees of freedom' concept (Watts 2004). Although not without controversy, many such systems are described as scale-free or scale-invariant and follow power law distributions (Kello et al. 2010). Scale-free systems are characterized by the property of criticality; that is, they sit on the cusp between completely predictable (rigid) and completely unpredictable (chaotic) behavior. This is precisely the state we noted above as useful for a system that needs to be both highly adaptive and yet stable; these properties have been described in brain networks at multiple scales, from local and large-scale circuits (Fiete et al. 2010; Kitzbichler et al. 2009; Rubinov et al. 2011) to cognitive behaviors as complex as language (Kello et al. 2010; Steyvers and Tenenbaum 2005), online collaborative interactions (Woolley and Hashmi 2013—this volume), and the phase shifts from wake to sleep (Bedard et al. 2006; Zempel et al. 2012).

Scale-free systems share a common architecture described in the seminal paper of Watts and Strogatz (1998) as a small world network. In this architecture, network elements (termed nodes) are linked by connections (termed edges) such that the majority of connections are local while there are only sparse linkages between distant elements (Butts 2009; Watts and Strogatz 1998). This architecture confers several important properties to the system, and points to interesting system behaviors. As it is this architecture that links human social organization and behavior to that of the brain network, a brief description of some of these properties will be provided along with references for those interested in learning more.

A characteristic of small world networks is the presence of hub elements—elements that are richly connected to other network elements—while the majority of elements are more sparsely connected (Eguiluz et al. 2005). This organizational feature has been shown to be present in the brain for both structural and functional linkages (Collin et al. 2013; van den Heuvel et al. 2012), and has formed the basis for designation of a set of linking hubs labeled as 'rich club' elements. The same feature has been shown to be critical to human social interactions, from dissemination of information via communication (Opsahl et al. 2008; van den Heuvel et al. 2012; Vaquero and Cebrian 2013) to the diffusion of disease epidemics (Christakis and Fowler 2008; Pastor-Satorras and Vespignani 2001; Zhang et al. 2011).

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These hub elements are critical to communication in small world networks as they provide the links between modules or communities in the global network. While many studies have relied upon analysis of network interactions in stable periods, the interactions described are dynamic, with both the structure of local communities and the links that bind them in flux on multiple time scales. No single node, whether human or neural, is embedded in only a single community, so that its behaviors are the result of both its structural embedding and the multirelational networks in which it operates.

The Computational Power of Human Social Communication

The concept of harnessing human elements for computation is not new (Grier 2005), and the practice of using humans as computational elements can be found as early as the eighteenth century. Modern computing has been argued to have developed from the intersection of scientific problem solving, technological innovation, and the social practice of computing teams (Rall 2006). Human computers calculated solutions to problems, often using pen and pencil but in later periods augmented with simple adding machines. In some instances, the human computers were well trained, but this was not always the case (Grier 1998, 2005; Rall 2006). While the period of human computers focused on calculating solutions to problems, as has been noted by others, the modern view of human computation rests on a partnership between electronic—or perhaps quantum—computers and humans in which each provides a unique skill set (Heylighen 2013).

One similarity remains as essential to the new view of human computation as it was to earlier views and that is the need to clearly and carefully define the problem at hand and the solution space within which it resides. While crowd-sourcing and citizen science are clear paths toward social modes of computation, they do not erase the need for expert knowledge and successful implementation of human computation will require a solid understanding of the social interrelationships needed to interleave expert and unskilled team members. This is not to suggest that, for example, all such teams are comprised of non-expert members—teams may also be composed of teams of interlinked experts in different arenas. However, regardless of the team composition, from the sheer number of individuals and computers involved to the skill sets of individual agents, social interaction and cultural biases must be understood to optimize any solution. Network analysis is one tool that may aid in this endeavor.

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The Psychopathology of Information Processing Systems

Matthew Blumberg and Pietro Michelucci

Introduction

If we organize human participants into systems modeled loosely on cognitive architectures (see Blumberg (2013), Heylighen (2013), Pavlic and Pratt (2013), all this volume), it is conceivable that such systems will exhibit dysfunction, just as humans do. And it therefore will be necessary to develop methods of thinking about, diagnosing, and treating (e.g. debugging) such issues.

Two approaches will be explored: the first views mental illness from the standpoint of communications theory and logical structure—essentially viewing mental illness as failure in information processing. The second views mental dysfunction from the standpoint of brain chemistry. Each maps somewhat differently to information processing systems—suggesting different modes of analysis and means of intervention.

The goal of this chapter is to discuss the nature of such systemic pathologies speculatively—we aim not to provide a rigorous analysis, but rather to begin a conversation.

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Part I: Interaction Dysfunction

Schizophrenia in Persons

What Is Schizophrenia?

Gregory Bateson describes a Schizophrenic as "a person who does not know what kind of message a message is." (Bateson et al. 1956). In broad terms, this means understanding the condition as being rooted in a failure to discern context; more rigorously it means understanding the condition as a specific patterned failure to keep straight the "logical type" of messages. From this perspective, what manifests as mental illness is at root a pathology of information processing.

The "Theory of Logical Types" (Whitehead and Russell 1927) is a formal way to describe what one might intuitively describe as "levels of abstraction" within a set of information. In this formalization, each item of a set is a member of a "class". A critical distinction is that a class cannot be a member of itself; nor can one of the members of the class be the class itself. That is, a "class" represents a higher level of abstraction—a higher logical type—than its "members". In other words: information is hierarchical.

A few examples illustrate this idea of "logical types" (Bateson 1979):

- The name is not the thing named but is of different logical type, higher than the thing named.
- The injunctions issued by, or control emanating from, the bias of a house thermostat is of higher logical type than the control issued by the thermometer. (The *bias* is the device on the wall that can be set to determine the temperature around which the temperature of the house will vary.)
- The word *tumbleweed* is of the same logical type as *bush* or *tree*: It is not the name of a species or genus of plants; rather, it is the name of a class of plants whose members share a particular style of growth and dissemination.
- *Acceleration* is of a higher logical type than *velocity*.

The use of Logical Typing can be seen to be fundamental to human communication. "Play", "non-play", "fantasy", "sacrament", "humor", "irony", and "learning" are all examples of *classes* of communication. In all these cases, proper interpretation of a specific message[1] depends upon proper identification of the Logical Type to which it belongs—i.e., proper identification of the *context* of the message.

By way of example, children may "Play" at fighting. While such activity may have many of the outward markers of "real" fighting, the participants can nevertheless engage without anger or malice. But if a participant for some reason comes to see the context of such interaction as "real" fighting, the meaning of events changes, and the actions may degrade to harmful violence.

[1] Note that "message" here is used in a general way: including verbal utterance, non-verbal action, absence of utterance or action, etc. Anything that can or should be taken as being of consequence in a social interaction.

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Returning to our thesis, Bateson defines a schizophrenic as one who (a) has difficulty in assigning the correct communicational mode to the messages he receives from other persons; (b) has difficulty in assigning the correct communicational mode to those messages which he himself utters or emits nonverbally; and/or (c) has difficulty in assigning the correct communicational mode to his own thoughts, sensations, and percepts. Most generally—"He has special difficulty in handling signals of that class whose members assign Logical Types to other signals."

In "Toward A Theory Of Schizophrenia", Bateson looks specifically at the role "Double Binds", situations in which messages implicit at different levels of communication conflict with one another. These experiences can be very difficult for affected persons to define, because conflict exists between *different levels of the same interaction*. For instance,

> A young man who had fairly well recovered from an acute schizophrenic episode was visited in the hospital by his mother. He was glad to see her and impulsively put his arm around her shoulders, whereupon she stiffened. He withdrew his arm and she asked, 'Don't you love me anymore?' He then blushed, and she said, 'Dear you must not be so easily embarrassed and afraid of your feelings.' (Bateson et al. 1956)

I.e., in this example the young man can become confused by the conflict between meanings implicit at different levels of the same interaction: the mother on the one hand stiffening when hugged, while at same time asking "don't you love me anymore?"; and this is made worse when the mother provides the young man with an incorrect attribution for his inner confusion ("Dear, you must not be so easily embarrassed by your feelings.")

The means by which such apparently small communication issues can lead to large scale pathology is in some sense analogous to how the flow if a river creates a canyon: not by brute force, but by the slow and persistent effect of the water's friction over time. Thus in the above example, imagine that young man, growing up, has been subject to millions of similarly muddled communications over his life—always in the vital emotional context of a parent-child relationship. The young man, seeking to make sense of the world, may thus learn to muddle the logical type of messages—as a means to adapt, to make sense of things. (It is, in a sense, a perfectly rational response to an irrational environment). And the child, having so learned, may take these interpretative habits into secondary relationships as well (including his relationship with himself).

Schizophrenia in Social Groups

In the above view, certain patterned failures in communication and interpretation lead to behavioral dysfunction. We wish to introduce, speculatively, the notion that similar patterns of communication within social groups will lead to similar dysfunction—at the group level. I.e., that there exist pathologies of information systems generally, which can be exhibited at multiple scales, individual or group.

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From the point of view described earlier, {1} Schizophrenia in an individual is understood to be rooted in the individual's inability "to know what kind of message a message is"; and {2} that this confusion is often related to repeated experience of double-binds. With this in mind, consider:

A characteristic feature of contemporary media has been the blending of news and entertainment; of advertising and news; of opinion and fact, of expert and amateur. That is: one who turns to media for information about the world literally does not know what kind of messages he is getting.

Similarly, American political discourse is frequently characterized by double-binds, often with each of the two primary political parties articulating conflicting messages about the nature of reality. For instance, a terrorist attack creates a bind, putting into conflict essential principles civil liberties with the desire for security.

The increasing unreliability of information type (is it news? entertainment? advertising?), frequently experienced with particular acuteness around issues presented by institutional parties as double-binds (ex the requirements of civil liberties vs security), can thus be recognized as a communications pattern very much like that experienced by the individual schizophrenic. And so it is perhaps not surprising that the adventurous cultural analyst might perceive comparable *symptoms* to be exhibited at the cultural level. I.e., one might consider contemporary culture to be exhibiting certain "schizophrenic" patterns—for instance: pervasive belief in conspiracy theories[2] (i.e. paranoia); a government with reduced capacity to take consistent action; economic dysfunction.

As problems from this point of view are understood to be rooted in deficiencies in communications, interventions would be similarly focused. Examples might include actions to strengthen the journalistic establishment; to alter forms of political discourse, especially to either minimize or explicitly recognize the double-binds; and perhaps to introduce "therapeutic" double-binds, the resolution of which would require denial of one or another element of a larger bind.

Part II: Organismal Dysfunction

Next we apply an organismic view to complex, distributed information-processing systems, endowing them with agency, such as goal-directed behavior, and a tendency toward homeostasis—an equilibrium state. This view permits us to adapt extant pharmacological treatment models of human behavioral dysfunction to neurosis in these distributed systems.

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[2] "About half the American public endorses at least one kind of conspiratorial narrative"—"Conspiracy Theories, Magical Thinking, and the Paranoid Style(s) of Mass Opinion". J. Eric Oliver and Thomas J. Wood, *Working Paper Series*, University of Chicago, 2012.

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An Associative View

In general, thought-processes in humans are influenced heavily by fundamental drives. According to drive theory (Seward 1956), any disturbance to the equilibrium state in a person *drives* the person to engage in thought processes leading to behaviors that restore homeostasis, to ensure survival. For example, dehydration gives rise to thirst, which drives a person to seek water (the goal state). This leads to a series of thoughts about how to obtain water that might involve planning and decision-making (see Busemeyer and Townsend 1993). Though drive theory is oft criticized for not addressing secondary reinforcers (such as money), it is still a useful general framework for this discussion because it provides a context for understanding the role of stress in reinforcing thought processes.

When an organism's equilibrium is disrupted, the distance between the current state and goal state increases, which causes stress. Stress places an organism into a heightened state of arousal, which can increase associative learning by causing connections between neurons to form more easily. This is generally considered adaptive because it enables more rapid experiential learning for lessons most relevant to survival.

Post-Traumatic Stress Disorder (PTSD)

However, extreme stress due to trauma and the consequent sudden and heightened learning can have deleterious effects, such as post-traumatic stress disorder (PTSD). In such cases, the brain states that coincided with the trauma are formed indelibly. The resultant associations are so strong that if those brain states or similar ones are reproduced by other means (external or internal), it can trigger an association to the traumatic event that stimulates a stress response comparable to the original experience. This stress response then further reinforces the association of the trigger event to the traumatic event and may even cause new associations to form that are unrelated to the original event. This self-perpetuating cycle creates an associative "gravity well" that can eventually link so many aspects of daily experience to stress that a person becomes effectively paralyzed by anxiety.

Consider, for example, a person who is mugged at gunpoint by someone wearing a ski mask. Subsequently, when the victim is approached in a new context by an actual skier wearing a ski mask that resembles the one worn by the mugger, he experiences tremendous anxiety. And since the post-traumatic anxiety is experienced in the novel context of ski slopes, the victim creates new stress associations to that context and, consequently, avoids skiing.

Fear Circuits

The networks of association between brain states and stress response are sometimes referred to as "fear circuits". These may be phylogenetic in origin, such as the innate

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fear of seeing one's own blood, or ontogenetic, such as the learned fear of hospitals (Bracha 2006). Importantly, these associations are generated by and apply to perceptual states, regardless of whether they correspond to an external world state, a dream state, or wakeful thought processes. Indeed, the Ancient Greek philosopher Epictetus (2004) made the prescient observation that "what bothers people is not what happens, but what they think of it."[3]

Obsessive-Compulsive Disorder (OCD)

While PTSD has a multi-faceted clinical presentation, including such symptoms as blackouts (memory loss), it is the manifestation of persistent, intrusive thoughts, or "obsessions" that is most germane to this discussion. Obsessive-compulsive disorder[4] (OCD) is often the diagnosis given to the presentation of such chronic rumination. The same notion of fear circuits attributed to PTSD applies also to OCD, but does not require a traumatic precursor event, and may involve more abstract concepts.

For example, the perception that a country is moving toward civil war could generate anxiety in a person that leads to obsession. The increased level of stress induces hyper-associative learning, such that any new thoughts would be more likely to be connected to the concept of civil war. For example, a typical shortage of food at the grocery store could be misconstrued as a sign of stockpiling in anticipation of a food shortage due to war.[5] This might link any food-related concepts to civil war such that any future meal preparation would activate the civil war fear circuit. Furthermore, food preparation itself would be incorporated into an expanding and self-reinforcing civil war fear circuit.

Treating OCD in Persons

Today, there are two accepted treatments for OCD: a behavioral treatment called cognitive-behavioral therapy [6](CBT) and pharmacological treatment. Herein, we focus on the latter. The most effective drugs for treating OCD are serotonin reuptake inhibitors (Simpson 2010), suggesting that a serotonin deficiency may be responsible for obsessive behavior. Serotonin is a neurotransmitter, a chemical messenger that supports communication among neurons in the brain. What is most relevant here is that these drugs are used in the treatment of all anxiety disorders, not just OCD.

[3] Special thanks to Ernesto Michelucci for re-popularizing this simple quote, which has deep implications for the human condition.

[4] Not to be confused with clinical perfectionism, which is sometimes referred to as obsessive-compulsive *personality* disorder (OCPD).

[5] Indeed, according to the Batesonian model described above, this could be described as simply another example of context misinterpretation.

[6] CBT involves overt associative remapping via exposure and response prevention.

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Though the specific mechanism by which serotonin alleviates OCD symptoms is not well-understood, it is the conjecture of this author that reducing anxiety attenuates the hyper-associative growth and reinforcement of fear circuits, thereby disrupting the rumination cycle. Without constant reinforcement, the fear circuits diminish over time at a normal rate of memorial decay. This interpretation suggests a computational proxy, discussed below, that might be effective for treating obsession in distributed cognitive systems.

A Problem-Solving Superorganism

A superorganism in its most general definition is simply an organism consisting of many organisms. The present discussion, however, is interested in superorganisms consisting of a technology-mediated collective of human (and possibly machine) agents, functioning collectively as a distributed information processing system. We also assume for this discussion that this system, like all organisms, seeks homeostatis. Thus, it has drives related to maintaining an equilibrium state and engages in goal-directed behaviors resulting from those drives. One example of such a system would be a massively distributed problem solving (Michelucci 2009) system in which very large numbers of people contribute to solving complex problems that exist in the real world (see Greene and Young (2013), this volume).

Let's further consider that communication among humans in this superorganism is mediated by a software-based workflow or cognitive architecture. Thus, the quality and quantity of information that flows among information processing agents is both monitored and influenced by the automated control system. Presuming the control system more heavily weights factors that lead most directly to a solution state, associations relevant to those factors would be reinforced most heavily.

Obsession in Superorganisms

So how would OCD manifest in such a superorganism. Consider that in such a problem-solving system "stress" would be characterized by a systemic assessment of distance between the current state and solution state for whatever problems are being addressed. For example, if the solution state is a stable earth climate, then the level of stress in the superorganism might correspond to the perceived distance between the current state and solution state. Thus, if agents within the system perpetuate the belief that industrial carbon dioxide emissions are causing climate change, the system would strengthen the association of carbon dioxide emissions to stress, leading to increased activity around solving the sub-problem of carbon dioxide emissions.

It is easy to imagine how such an association could then lead to further associations to carbon-dioxide emission such as human respiration, which itself could subsequently lead to the more general observation that all animal respiration adds the

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"stress" of climate change. While this association may be valid in terms of first-order effects, it would ignore systemic effects. And if the associations were made too strongly due to the perceived influence of carbon dioxide emissions on climate change-related stress in the system, the problem-solving resources of the system could become pathologically overcommitted to resolving that carbon dioxide sub-problem. In other words, the system could be obsessed with reducing carbon dioxide emissions to the negligence of a more holistic solution that takes a more balanced view of the multifaceted nature of the problem.

Treating OCD in Superorganisms

Indeed, such group-based obsession occurs also in natural social systems, as described in Part I, though in such cases, the only recourse may be behavioral—that is, policy-based. Engineered systems, however, afford a recourse that might not otherwise exist. Access to the controlling software would make it possible to both observe and adjust the rules that govern the strengths of associations among individual agents in the distributed problem solving system. Decreasing the extent to which systemic stress influences collaborative activities among agents could help restore balance to distributed thought processes. Indeed, it is conceivable that just as with humans, whereby minor changes in neurotransmitter levels can give rise to significant changes in behavior, small calibrations to parameters that govern association strength in distributed problem solving algorithms could resolve obsessive behavior in superorganisms. Whether agents within the system acting would make such calibrations as implementers of an executive function, by a completely automated homeostatic algorithm, or by some external "superorganism psychiatrist" depends upon the evolution of these systems and the co-development of treatment models.

When Superorganisms Are Not Organisms

We should not ignore the possibility that other sorts of pathology may exist in superorganisms that don't in humans because superorganisms are fundamentally different than humans—they are themselves composed of interconnected highly complex organisms. Indeed, superorganisms are a different *logical type* than humans. A superorganism is a system of complex systems, which could give rise to entirely new and unprecedented classes of behavior dysfunction. Since we do not know what to look for, we may not at first be cognizant of the emergence of such dysfunction. And once we do become aware, we may need to develop new treatment models and methods specific to those needs. Given the potential impact of such dysfunction, it would behoove us to minimize the potential for disruptive surprise by developing our understanding of superorganismic behavioral pathology in close parallel with the development of superorganisms themselves.

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Conclusion

The reader may or may not accept various portions of the above speculation, or may consider the discussion far too incomplete in its presentation for serious consideration. The point we hope will nevertheless be of interest, however, is that at an individual level, mental pathology can be seen to result from patterned defects in communication and learning; and that similar defects within a culture or future engineered social system may result in similar behavioral patterns at the larger group level. Indeed, the latter may contribute significantly to the former.

If true, one may aspire to develop means to identify and diagnose such information processing defects; and to develop interventions to prevent, minimize, or eliminate the defects or their symptoms.

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Information and Computation

Carlos Gershenson

Introduction

Before delving into the role of information theory as a descriptive tool for human computation (von Ahn 2009), we have to agree on at least two things: what is human, and what is computation, as human computation is at its most general level computation performed by humans. It might be difficult to define what makes us human, but for practical purposes we can take an "I-know-it-when-I-see-it" stance. For computation, on the other hand, there are formal definitions, tools and methods that have been useful in the development of digital computers and can also be useful in the study of human computation.

Information

Information has had a long and interesting history (Gleick 2011). It was Claude Shannon (1948) who developed mathematically the basis of what we now know as *information theory* (Ash 1990). Shannon was interested in particular on how a message could be transmitted reliably across a noisy channel. This is very relevant for telecommunications. Still, information theory has proven to be useful beyond engineering (von Baeyer 2005), as anything can be described in terms of information (Gershenson 2012).

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A brief technical introduction to Shannon information *H* is given in Appendix A. The main idea behind this measure is that messages will carry more information if they reduce uncertainty. Thus, if some data is very regular, i.e. already certain, more data will bring few or no new information, so *H* will be low, i.e. few or no new information. If data is irregular or close to random, then more data will be informative and *H* will be high, since this new data could not have been expected from previous data.

Shannon information assumes that the meaning or decoding is fixed, and this is generally so for information theory. The study of meaning has been made by semiotics (Peirce 1991; Eco 1979). The study of the evolution of language (Christiansen and Kirby 2003) has also dealt with how meaning is acquired by natural or artificial systems (Steels 1997).

Information theory can be useful for different aspects of human computation. It can be used to measure, among other properties: the information transmitted between people, novelty, dependence, and complexity (Prokopenko et al. 2009; Gershenson and Fernández 2012). For a deeper treatment of information theory, the reader is referred to the textbook by Cover and Thomas (2006).

Computation

Having a most general view, computation can be seen simply as the transformation of information (Gershenson 2012). If anything can be described in terms of information, then anything humans do could be said to be human computation. However, this notion is too broad to be useful.

A formal definition of computation was proposed by Alan Turing (1936). He defined an abstract "machine" (a Turing machine) and defined "computable functions" as those which the machine could calculate in finite time. This notion is perhaps too narrow to be useful, as Turing machines are cumbersome to program and it is actually debated whether Turing machines can model all human behavior (Edmonds and Gershenson 2012).

An intermediate and more practical notion of computation is *the transformation of information by means of an algorithm or program*. This notion on the one hand tractable, and on the other hand is not limited to abstract machines.

In this view of computation, the algorithm or program (which can be run by a machine or animal) defines rules by which information will change. By studying at a general level what happens when the information introduced to a program (input) is changed, or how the computation (output) changes when the program is modified (for the same input), different types of dynamics of information can be identified:

- Static. Information is not transformed. For example, a crystal has a pattern which does not change in observable time.
- Periodic. Information is transformed following a regular pattern. For example, planets have regular cycles which in which information measured is repeated every period.

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- Chaotic. Information is very sensitive to changes to itself or the program, it is difficult to find patterns. For example, small changes in temperature or pressure can lead to very different meteorological futures, a fact which limits the precision of weather prediction.
- Complex. Also called critical, it is regular enough to preserve information but allows enough flexibility to make changes. It balances robustness and adaptability (Langton 1990). Living systems would fall in this category.

Wolfram (2002) conjectured that there are only two types of computation: universal or regular. In other words, programs are either able to perform any possible computation (universal), or they are simple and limited (regular). This is still an open question and the theory of computation is an active research area.

Computing Networks

Computing networks (CNs) are a formalism proposed to compare different types of computing structures (Gershenson 2010). CNs will be used to compare neural computation (information transformed by neurons), machine distributed computation (information transformed by networked computers), and human computation.

In computing networks, nodes can process information (compute) and exchange information through their edges, each of which connects the output of node with the input of another node. A computing network is defined as **a set of nodes** N **linked by a set of edges** K **used by an algorithm** a **to compute a function** f (Gershenson 2010). Nodes and edges can have internal variables that determine their state, and functions that determine how their state changes. CNs can be stochastic or deterministic, synchronous or asynchronous, discrete or continuous.

In a CN description of a **neural network** (NN) model, *nodes* represent neurons. Each neuron i has a continuous state (output) determined by a function y_i which is composed by two other functions: the weighted sum S_i of its inputs $\overline{x}_i$ and an activation function A_i, usually a sigmoid. Directed *edges* $i\,j$ represent synapses, relating outputs y_i of neurons i to inputs x_j of neurons j, as well as external inputs and outputs with the network. Edges have a continuous state $w_{i\,j}$ (weight) that relates the states of neurons. The *function* f may be given by the states of a subset of N (outputs $\overline{y}$), or by the complete set N. NNs usually have two dynamical scales: a "fast" scale where the network function f is calculated by the functional composition of the function y_i of each neuron i, and a "slow" scale where a learning *algorithm* a adjusts the weights $w_{i\,j}$ (states) of edges. There is a broad diversity of algorithms a used to update weights in different types of NN. Figure 1 illustrates NNs as CNs.

Digital machines carrying out **distributed computation** (DC) can also be represented as CNs. *Nodes* represent computers while *edges* represent network connections between them. Each computer i has information H_i which is modified by a program $P_i(H_i)$. Physically, both H_i and P_i are stored in the computer memory, while the information transformation is carried out by a processor. Computers can share

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Fig. 1 A NN represented as a CN

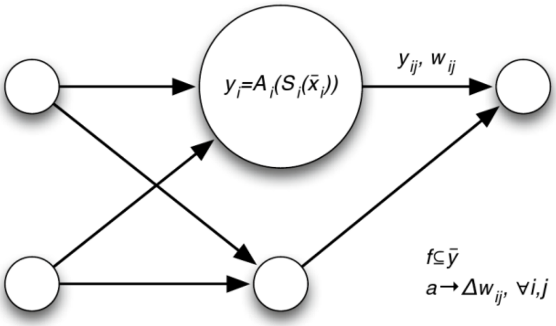
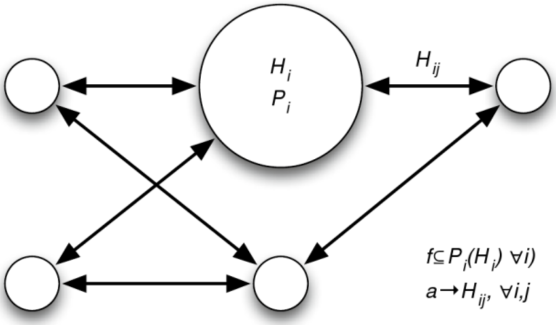


Fig. 2 A DC system or a HC system represented as a CN



information H_{ij} across edges using a communication protocol. The *function f* of the DC will be determined by the output of $P_i(H_i)$ of some or all of the nodes, which can be seen as a "fast" scale. Usually there is an algorithm a working at a "slower" scale, determining and modifying the interactions between computers, i.e. the network topology. Figure 2 shows a diagram of DC as a CN.

Human computation (HC) can be described as a CN in a very similar way than DC. People are represented as *nodes* and their interactions as *edges*. People within a HC system transform information H_i following a program $P_i(H_i)$. In many cases, the information shared between people H_{ij} is transmitted using digital computers, e.g. in social networks, wikis, forums, etc. In other cases, e.g. crowd dynamics, information H_{ij} is shared through the environment: acustically, visually (Moussaïd et al. 2011), stigmergically (Doyle and Marsh 2013), etc. The function f of a HC system can be difficult to define, since in many cases the outcome is observed and described only a posteriori. Still, we can say that f is a combination of the computation carried out by people. An algorithm a would determine how the social links change in time. Depending on the system, a can be slower than f or vice versa.

In DC, the algorithm a is centrally determined by a designer, while in most HC systems, the a is determined and executed by people (nodes) themselves.

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Appendix

Shannon Information

Given a string X, composed by a sequence of values x which follow a probability distribution $P(x)$, information (according to Shannon) is defined as:

$$H = -\sum P(x)\log P(x). \tag{1}$$

For binary strings, the most commonly used in ICT systems, the logarithm is usually taken with base two. For example, if the probability of receiving ones is maximal ($P(1) = 1$) and the probability of receiving zeros is minimal ($P(0) = 0$), the information is minimal, i.e. $H = 0$, since we know beforehand that the future value of x will be 1. Information is zero because future values of x do not add anything new, i.e. the values are known beforehand. If we have no knowledge about the future value of x, as with a fair coin toss, then $P(0) = P(1) = 0.5$. In this case, information will be maximal, i.e. $H = 1$, because a future observation will give us all the relevant information, which is also independent of previous values. Equation 1 is plotted in Fig. 3. Shannon information can be seen also as a measure of uncertainty. If there is absolute certainty about the future of x, be it zero ($P(0) = 1$) or one ($P(1) = 1$), then the information received will be zero. If there is no certainty due to the probability distribution ($P(0) = P(1) = 0.5$), then the information received will be maximal. Shannon used the letter H because equation 1 is equivalent to Boltzmann's entropy in thermodynamics, which is also defined as H. The unit of information is the bit. One bit represents the information gained when a binary random variable becomes known.

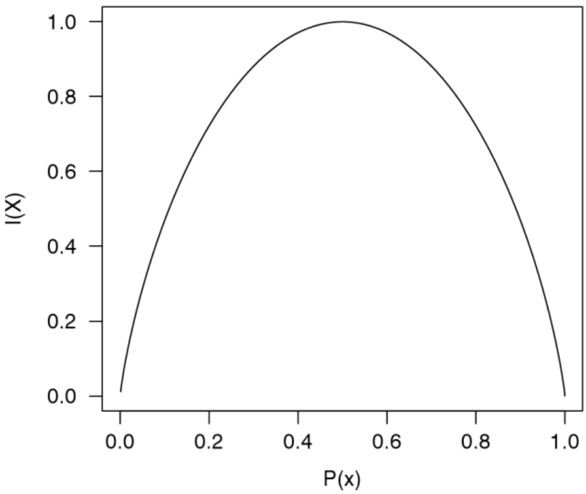

Fig. 3 Shannon's information $H(X)$ of a binary string X for different probabilities $P(x)$. Note that $P(0) = 1 - P(1)$

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A more detailed explanation of information theory, as well as measures of complexity, emergence, self-organization, homeostasis, and autopoiesis based on information theory can be found in Fernández et al. (2013).

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Epistemological Issues in Human Computation

Helmut Nechansky

Defining Epistemology

Traditional Epistemology is the branch of philosophy concerned with individual human knowledge, its base, its content and its validity. The focus on the individual results from the fact that there is no knowledge without an individual carrier.

There is no unequivocal definition of knowledge yet, but there is some shared understanding that knowledge is determined by the following four aspects: (1) The human senses and the human mind form its structural base; This base determines (2) what can become its possible content; (3) This content may or may not amount to a representational model corresponding to the world external to the individual carrier; (4) If the content does amount to a valid representational model can be confirmed by repeated observation of a correspondence with the external world, by observation of predicted states, and by goal-orientated actions leading towards predicted goal-states.

Social epistemology adds that the knowledge of any single individual depends on and is interrelated with the knowledge of other individuals, since any human is born, brought up and mostly lives in a social world. Therefore individual knowledge cannot be studied alone.

There are many other branches of epistemology we cannot mention here due to limitations of scope and space. The Internet Encyclopedia of Philosophy (2013) and the Stanford Encyclopedia of Philosophy (2013) offer the easiest access to this wide field, while Goldman (1999) offers an interesting discussion. However, this chapter provides a context sufficient for understanding the role of epistemology in human computation.

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The Role of Epistemology

Epistemology as a branch of philosophy may seem outdated in a time of 'knowledge society', of cloud computing, and human computation. But this is not the case, since we do not yet have an unequivocal, agreed on, scientific definition what actually constitutes 'knowledge'. So any dealing with knowledge is ultimately still a philosophic endeavor.

And knowledge is the base of all our actions. Questions about this base arise often: How do we know? What can we know? Is this knowledge valid? Is it complete, i.e. sufficient to reach a goal? These are *epistemological* questions at the core of all human endeavors. Usually they do not get the attention they would deserve. And the more complex the systems, on which we rely, become, the more important become *answers* to these questions.

A Cybernetic Approach to Main Aspects of Epistemology

Cybernetics is the general theory of control in technical, biological and sociological systems. Control is pursuing and maintaining a goal-value, i.e. a certain physical state, against a changing environment, i.e. against physical influences disturbing that state. The process of control consists of (a) observing the environment with sensors, (b) comparing the sensor data with a goal-value and (c) deciding for an action to achieve that goal. Standard example for that process is a temperature controller, which aims at a desired room temperature as goal-value; to achieve that it (a) observes the current temperature, (b) compares it with the desired room temperature and (c) decides between the actions "heating" or "cooling" to achieve that.

In the following we will consider humans as complex controller structures. Here the brain has *in principle* controller functions similar to a temperature controller, but in much larger numbers and much more complex forms. Primarily the brain has to enable survival by maintaining some existential goal-values (necessary air, water and food supply; the body temperature). To achieve that it has (a) to observe the state of the environment, (b) to compare if that state serves the existential goal-vales, and (c) to decide for actions to enable that. Secondarily the brain has additional controller functions, which enable making a model of the environment, and, based on that, making predictions, concepts and setting long-term and short-term goal-values. To realize these future goal-values the brain again carries out the controller functions of (a) observing the environment, (b) checking if it corresponds to the goals and (c) deciding for actions to make it so.

Of course, the preceding description of brain functions is a crude simplification (for some important underlying complexities see Nechansky 2012a, b, 2013a, b), but we do maintain that the brain has primarily controller functions. For reasons of brevity we consider here just a few of these controller functions, each illustrating an epistemological problem. We will first describe these controller functions for individuals (illustrating the core problems of traditional epistemology) and then analyze

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predictions of possible future states and events from known sequences or interrelated sequences of patterns.

Models can be confirmed by repeated observations, by observing predicted states, and by goal-orientated actions leading towards predicted goal-states.

Model based predictions are used for two different types of further decisions, leading to two different kinds of feedback loops—one internal and the other external:

Decisions for goal-values: Predictions may be occasionally used to set long-term or short term goal-values (see above). This is an *internal* feedback loop. Here primarily existential goal-values are applied to make decisions for long-term goal-values (e.g. trying to make a living within a certain profession). Then secondarily these long-term goals are used to make decisions for short-term goals. So decisions for goal-values are primarily related to the existential goal-values and create secondarily a hierarchy of subordinated goal-values, by adding, changing or deleting long-term and short term goals.

This is the most important and least understood process of individual epistemology. It determines the entire further behavior of the individual: The previously set goal-values determine directly what is considered important in *modeling decisions* (see above), i.e. which models are made, and indirectly which predictions become possible and which *decisions for actions* (see below) are made.

Decisions for actions: Normally predictions derived from models are just used to trigger one of the effectors (muscles generally, but mainly arms, hands, legs, feet or mouth) to take an appropriate physical action or to start a communication. This is the usual *external* feedback loop, trying to change the external world in some way towards a goal-value.

So the goal-value (whether existential, long-term, or short-term) currently applied determines which action to choose (e.g. to eat, work or communicate, etc.).

Effector Outputs: Decisions for actions trigger the effectors to cause external effects, either physical actions or communication, i.e. primarily words, addressing other individuals.

In summary, these two feedback loops work as follows: Humans make observations of their environment. Based on that, they make primarily models that serve their existential goals. From learning what serves these needs best they secondarily derive models to serve long-term and short-term wants. The sum of these goal-values for needs and wants determines their *modeling decisions* and their *decisions for actions*, i.e. their entire further individual behavior.

Aspects of Social Epistemology

Now let us apply this controller model of a human to the interaction of two individuals (see Fig. 2). This illustrates the problems of social epistemology:

An interaction starts when individual A acts towards B. B observes these actions and evaluates the corresponding sensor inputs in relation to currently important

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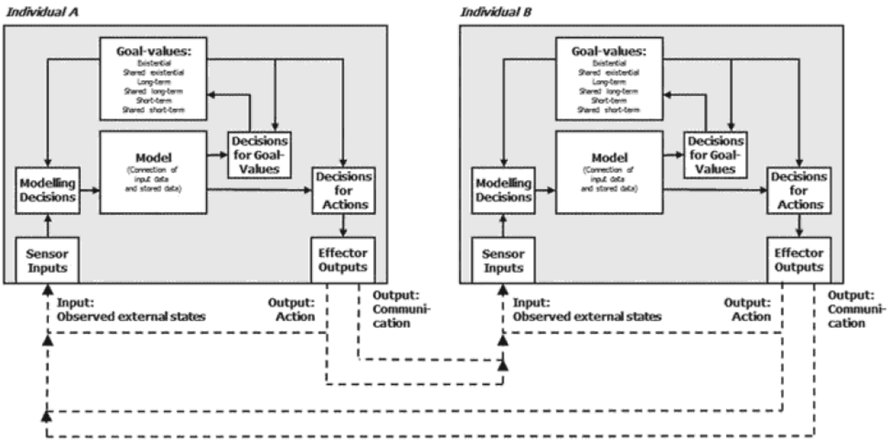

Fig. 2 Aspects of social epistemology: interactions can lead to individual decisions for shared goal-values

goal-values (existential, long-term, short-term). Making a *modeling decision* (see above) B develops a model of A's behavior, predicts its usefulness or danger, and decides for an appropriate action. Then A runs the same process in relation to B's response.

Repetition of this basic exchange may cause at some point in time a *decision for goal-values* (see above) in A and/or in B: Repeated usefulness of A's behavior will cause B to consider A as predictably 'good' or 'interesting'. Then B may decide to add goal-values referring to A to the list of B's already given individual goal-values. Now A may, but need not do the same.

Ideally, of course, this process leads to the development of *shared goal-values* (existential, long-term or short-term), which all interacting parties agree on and add to their individual goal-values. The basic form of this process is realized, of course, in the upbringing of a child. Here the parents serve the needs of the child. So the child will develop shared goal-values with the parents.

Let us mention that the development of shared goal-values may happen spontaneously (e.g. when people face the same problem or threat).

Or this process may be skipped, because interacting people already came independently to shared goal-values (e.g. the same interests or profession).

But mostly, shared goal-values result just from stipulating reciprocally advantageous exchanges of goods, or services, or money and labor, etc.

On the other hand shared goal-values may be propagated by manipulation (A may control the data available to B, using e.g. advertising, censored news, political propaganda, etc.; thus A can limit what may enter into B's models); or they may be enforced to a certain degree (A may have power to control B's access to

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important resources, like income, etc., or may even be able to apply force; thus A can make B subordinate to and serve his or her goal-values).

The general constraint on developing shared goal-values is the scarcity of goods or societal positions (A and B cannot eat the same bread, or fill the same position in a hierarchy, etc.). Therefore individual goal-values do remain important.

Once parties do share goal-values this will lead to similarities in *modeling decisions* (see above). So they will consider similar data as relevant, will remember and store similar data, and will be interested in making similar models containing certain sequences of cause and effect and enabling particular predictions. Shared goal-values will lead, too, to similar *decisions for actions* (see above).

Shared goal-values will only lead to similar, but not equal, models, as long as the parties rely just on their individual modeling decisions and model making. Only if they cooperate to make externalized mutual verbal concepts, plans, computer programs or mathematical models, they can get to increasingly equal or even unequivocal models.

In summary social epistemology is about human interactions, which make individuals activate their *internal feedback loop for decisions for goal-values*, the process least understood in individual epistemology. The best result is that A and B end up with *individual as well as some shared some goal-values*. And whenever they apply shared goal-values in their current decisions for actions, they will cooperate.

Individuals and Computers: Structures and Interactions

Now let us introduce computers into the relationship of the individuals A and B (see Fig. 3). We characterize computers as controller structures, too, which, of course, differ from humans:

The main differences are: (a) Computers work usually with *fixed* goal-values set by the programmer (we show that in Fig. 3 with the bold arrows directly setting goal-values). So (b) computers lack the *internal feedback loop for making decisions for goal-values*. (In machine learning we occasionally allow computers to make decisions for short-term goals. But we definitely do not want a computer to change its long-term goal-values by itself, so that e.g. a computer programmed to analyze climate data decides on its own to analyze some other data.)

The *external feedback loop* of humans and computers is widely similar: Computers also have sensor inputs (via a keyboard, sensors or data lines). They apply *modeling programs* (matching human *modeling decisions*, but with fixed goal-values) and derive *models* from them (containing here mainly data and mathematical functions, which represent external patterns and sequences), which are used to make predictions. Based on these predictions *programs deciding for actions* are applied (again matching human *decisions for actions* with fixed goal-values).

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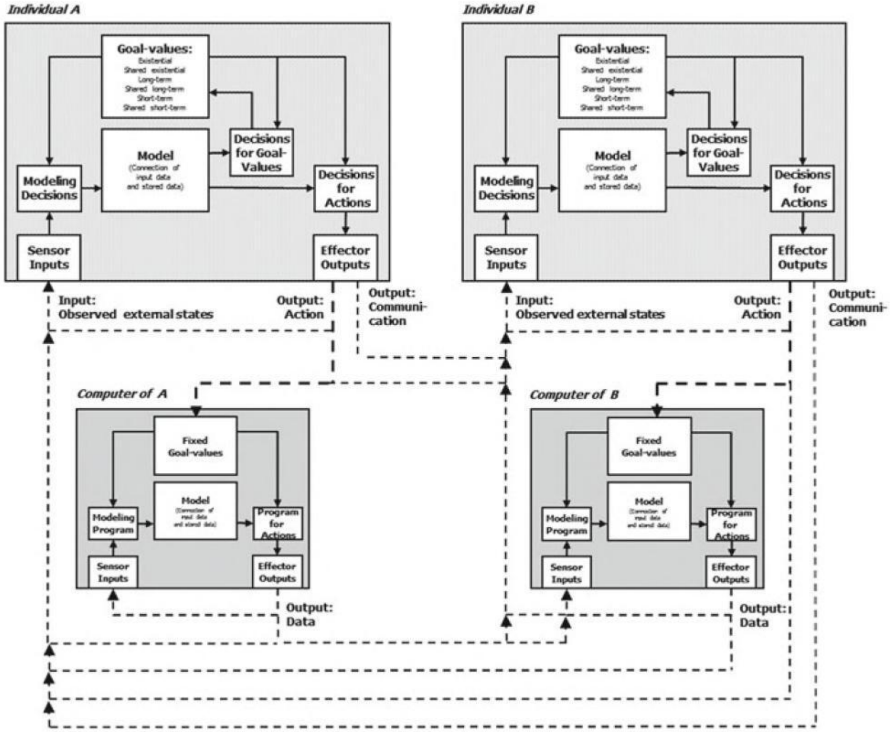

Fig. 3 Individuals and computers: interaction channels added to the context of social epistemology

The *effector outputs* are actions like sending data to other computers, controlling some technical device, or making printouts for human users, etc.

If we take this basic scenario with two individuals and two computers n—times, to match a network, we will get hierarchies (Nechansky 2008) of individuals and computers. We cannot detail that here. We can only assert that this does not change the involved basic epistemological processes.

The Epistemic Processes of Human Computation

Now let us apply all we developed above to human computation:

A human computation project starts with an *initiation phase*, when an initiator defines the long-term goals and short-term tasks. Since human computation is generally applied to problems that require some human contribution, reaching these goals includes tasks that computers cannot yet perform. So the usual advantage of

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computers we emphasized in section "Individuals and Computers: Structures and Interactions", that they can be directly programmed to work towards a goal, is not available here.

Therefore collaborators have to be sought. The long-term goals and short-term tasks have to be communicated to them. They have to agree on them. And then they have to make *individual decisions for values*, accepting them as *shared goal-values*. We cannot overemphasize that:

1. The success of a human computation projects depends widely on the precise descriptions of long-term goals and short-term tasks, so that the collaborators can understand them and can later make the appropriate individual *modeling decisions* (see above).
2. So the decisive step of a human computation project is a successful finalization of the basic process of social epistemology, as discussed in section "Aspects of Social Epistemology", leading to the acceptance of shared goal-values. Persons focused too much on computation may easily overlook that.

   Dividing a project into subprojects may, but need not weaken that requirement: Now shared goal-values are just needed for the subprojects. But some people might deny contributing, because they do not share the goal-values of the whole project (e.g. a pacifist might deny to contribute to a subproject of a military project).

Once collaborators are found the *computation phase* of the project can start. It may take various forms (see e.g. Quinn and Bederson 2011), which may use any of the possible interconnections between individuals and their computers shown in Fig. 3.

After data acquisition and data distribution, the decisive step is, of course, the human evaluation of the data. Here the short term task of the human contributors is to make *modeling decisions*, judging if data meet the goal-values of the project (e.g. if pictures contain certain patterns, or data sets belong to a certain category, etc.). As emphasized above, the quality of this step depends primarily on clarity of goal-values, i.e. the preceding initiation phase. But it is important, too, that the collaborators do not have any conflicts of interest, i.e. that no other competing long-term and short-term goal-values influence them in their *modeling decisions*. So the success of the project depends to a large degree on the precise consideration and crafting of goal-values the collaborators can fully agree on. More on the importance of goal setting, and its interrelation with motivation and task performance, can be found in Locke's and Lathan's (1990, 2002) classic works on organizational psychology.

After the collection of the results from the collaborators questions of quality control arise. Some evaluation of the results by the initiator must be performed to check if the contributors acted as expected. Since computation is not directly available for obvious reasons, this can only be done indirectly, with approximate use of computers, applying statistics, employing experts, or another round of human computation. Anyway the understanding of the decisive *individual modeling decisions* of the contributors remains vague. So the validity of results obtained using this method remains in question.

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Synthesis and Taxonomy of Human Computation

Pietro Michelucci

Introduction

Human Computation is an emerging, multidisciplinary field spanning communities. Broadly, it refers to human participation in computational systems and the information and capabilities that arise from that. Beyond this general definition, however, there is a tendency for multiple and sometimes conflicting perspectives, as well as confusion. Therefore, this chapter seeks to characterize the conceptual space of human computation by defining key terminology within an evolving taxonomy.

Previous efforts have sought to flesh out the conceptual space of human computation (Law and Von Ahn 2011) and related terminology (Quinn and Bederson 2011). The present effort seeks to update this body of work in the context of new research and broader multidisciplinary context.

Key Concepts

Two key concepts are described here that provide a context for interpreting and understanding the definitions that follow.

Goals and Intentionality

Human computation (HC) systems are purposeful. They are driven by outcomes that derive from individual behavior, such as enjoyment from playing a game (see Celino; Ghosh; Sanfilippo et al., all this volume) or payment for completing a task (see Chandler

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et al., this volume). They are also driven by outcomes that derive from collective behavior or interactions, such as the advancement of science that results from citizen science projects (see Lintott, this volume). Furthermore, the locus of intentionality in human computation systems may be individual or collective. For example, an individual may launch a crowdsourcing campaign to satisfy a personal objective. Or a system's behavior may be driven by goals that are defined collaboratively by system participants.

Two related ideas emerge from this conceptual framing: emergent HC and engineered HC. Emergent HC refers to systems in which collective behavior is a natural consequence of individual behaviors; and may help inform a deeper understanding of individual behaviors in the context of system dynamics. Engineered HC refers to the notion of overtly creating a context in which the interaction of individuals within will give rise to desired systemic behavior. Though the emergent/engineered dichotomy is being introduced in this volume, the underlying concept is relevant both to understanding the scope of human computation and the relatedness of the terms that follow. Estrada and Lawhead (this volume) introduce the related concepts of natural, stable, and disruptive human computation, which also seem to be useful concepts for further partitioning the space of HC systems.

Computation = Information Processing

The relationship between computation and information processing has been a subject of some controversy. These terms have been differentiated on the basis of historical usage in theoretical contexts (see Piccinini and Scarantino 2010). However, the construal of computation as being equivalent to information processing seems to best fit the practical context of human computation.

In HC, "computation" refers not just to numerical calculations or the implementation of an algorithm. It refers more generally to *information processing*. This definition intentionally embraces the broader spectrum of "computational" contributions that can be made by humans, including creativity, intuition, symbolic and logical reasoning, abstraction, pattern recognition, and other forms of cognitive processing. As computers themselves have become more capable over the years due to advances in AI and machine learning techniques, we have broadened the definition of computation to accommodate those capabilities. Now, as we extend the notion of computing systems to include human agents, we similarly extend the notion of computation to include a broader and more complex set of capabilities.

It is this sense of computation that is intended in the definitions that follow.

Key Terminology

This chapter seeks to define key terms, which have been selected on the basis of prevalence in the book and broad usage across sub-disciplines. These definitions derive from prior work, lively collegial discourse, and the application of basic inference to a growing set of related concepts. It goes without saying that the meaning of terms evolves

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through usage. For maximal relevance herein, current popular usage *as applied to the study and practice of human computation* exerts considerable bias on these definitions. For this reason, you may discover that in some cases canonical meanings have been deprecated. Given the diversity of the community, context-based usages, and dynamic nature of the conceptual space in a rapidly growing field, it is unlikely that this set of definitions will meet with unilateral agreement. However, this chapter seeks to represent the most common views and, in certain cases, multiple views when there are divergent semantic tracks. For brevity of exposition, we do not belabor etymology, but instead seek to provide the reader with an accessible point of reference.

Glossary

Term	Definition
Collective Action	Human computation in which individual behaviors contribute to a collective product that benefits all members of the collective (see Novak, this volume).
Collective Intelligence	A group's ability to solve problems and the process by which this occurs.
Crowdsourcing	The distribution of tasks to a large group of individuals via a flexible open call, in which individuals work at their own pace until the task is completed (see Chandler, this volume).
Distributed Cognition/Collective Cognition	"The use of information technologies to make distributed information processing by humans much more powerful, focused and efficient" (see Heylighen, this volume).
Distributed Intelligence	The problem-solving capacity of distributed cognitive systems (see Heylighen, this volume).
Distributed Problem Solving	The application of massively distributed cognitive systems to solving problems (see Greene and Thomas, this volume).
Distributed Thinking	The effective distribution and coordination of information processing tasks among human computational agents informed by cognitive architecture (see Blumberg, this volume).
Human Computation/ Distributed Human Computation	1. The design and analysis of multi-agent information processing systems in which humans participate as computational elements. 2. The subset of systems theory in which the systems are composed of machines and humans connected by communications networks.
Organismic Computing	Augmented human collaboration characterized by shared sensing, collective reasoning, and coordinated action (see Michelucci, this volume).

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Participatory Sensing	The human-use of sensor-enhanced devices for spatially distributed data collection, enabled by pervasive computing (see Lathia, this volume).
Social Computing	Information processing that occurs as a consequence of human social interaction, usually assumed to occur in an online medium. Note: there is some debate in the field about how to classify systems in which behavior relies upon social knowledge or judgment but does not involve social interaction among participants.
Social Informatics/ Social Network Analysis	The use of big data to understand social behavior (see Lerman, this volume); in Social Network Analysis the "big data" is presumed to originate from behavioral data derived from technology-mediated social systems.
Superorganism	1. Individual organisms functioning together to support the objectives of the collective (see Pavlic and Pratt, this volume). 2. "A collection of agents which can act in concert to produce phenomena governed by the collective" (Kelly 1994).

Conclusion

This synthesis of key concepts in human computation is a snapshot. It is expected that the usage of these terms and related concepts will evolve with the discipline. Thus, this glossary should be revisited and refined by the community as necessary to best support fluid communication and broad comprehension across sub-disciplines.

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Part II
Application Domains

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The vibrant development of human computation over the last few decades has continued through the development of fielded systems that integrally involve people, increasing the leverage we can gain by studying and learning from this growing body of human computation applications. The goal of the chapters in this “applications” section of the handbook is to assemble a record of recent human computation applications to help further drive our understanding of the field.

For example, the widespread access to computing and communications technologies has created a wave of human computation innovations in service of humanitarian aid and disaster response. Patrick Meier starts this section by presenting six examples of human computation applications in this area over the period of 2010–2013. In addition to documenting these wonderful examples of human computation in the service of societal good, Meier also considers what we more general lessons we can learn from them and identifies directions for the future that they suggest.

A second example arises in the medical sector, where human computation innovations are changing the face of healthcare, often driven by the patients themselves bypassing the traditional medical enterprise. Caring for one’s health, particularly in the face of life-changing illness, continues to motivate those impacted by illness to push the envelope of what technology and network-based social interaction can achieve in health and medicine. Wicks and Little present a tour of some of the most important human computation innovations taking place in the medical sector. Again, importantly, they learn from this history of success to suggest what implications these examples may have for the future.

A third example occurs as we attempt to get the diverse knowledge of our world into computer-based form. Whereas the World Wide Web contains semi-structured information largely crafted for human consumption, the goal of the Semantic Web is to create a parallel infrastructure that stores information in ways that include some sense of the meaning of the information in computer-manipulable form. Getting vast amounts of semantically represented information in accurate, online form requires massive effort. Simperl, Acosta, and Flöck’s chapter provides a comprehensive survey of how people have built a range of human computation systems to facilitate various facets of this work. Their chapter shows how different human computation design patterns, particularly those of games-with-a-purpose and paid micro-labor, have had particular traction in this domain. They also suggest directions for the future, especially in terms of going beyond the generation of new systems and instead reusing and coupling the different ideas developed thus far.

Three chapters in this section concern “citizen science,” the process of scientific inquiry that in whole or part includes participants who are not professional scientists and often have far more limited training than professional scientists. Lintott and Reed present an overview of human computation in citizen science, especially from the perspective of their work on Galaxy Zoo, which has hundreds of thousands of participants and contributed new knowledge via dozens of scientific publications. They furthermore document their insights arising from their generalizing beyond Galaxy Zoo in the creation of the Zooniverse platform, which now includes dozens of projects in domains ranging from astronomy to zoology, especially so as to be able to scale to increasing numbers of people and use worker effort wisely, support

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open-ended investigation by participants, leverage complementary functionalities of machine learning, and ultimately stay in tune with motivations and knowledge of the people who participate in such projects.

Beal, Morrison, and Villegas complement such consideration of human computation in citizen science by also considering the learning opportunities that participation in such projects can provide. They focus on a case study, the Biosphere 2 Evapotranspiration Experiment, which brings middle and high school students to a project studying the loss of water from soil and the leaves of vegetation while also providing them with educational experiences in this domain.

In a series of related case studies, Lin et al. consider the application of distributed human computation to the problem of search and discovery, and in particular, toward the use of collective perception to find loosely-defined things. In this context they discuss first their experiences in the "Expedition: Mongolia" project, in which tens of thousands of participants contributed more than two million pieces of information to detect archaeological anomalies within massive quantities of high-resolution multi-spectral imaging data. They then describe subsequent related efforts in disaster assessment and search and rescue. The chapter concludes with tantalizing ideas about how to enhance the existing approach by tightly integrating human inputs with machine learning methods.

The transformative opportunities for computing and communications technologies have not been lost on those in the creative arts, where numerous innovative human computation ideas have been and are being explored. Rettberg's chapter provides an overview of key examples of human computation in electronic literature and digital art. Moreover, Rettberg focuses on lessons that appear when human computation is viewed from a digital literary perspective, especially in terms of the statements they make about the relative roles of and relationship between computing and people. Rettberg also shows us that the end goal of some of these examples of human computation are not be the direct outcome of their organized labor but rather they are particularly designed to make a point, to serve as a meta-critique of the values that may underlie human computation.

As we develop a greater number of human computation systems, gaining a better understanding of their relative strengths and weaknesses—across different methods, and in comparison to possible automated methods—grows in importance. Harris and Srinivasan use the task of query refinement in information retrieval as a platform to study the relative benefits of two forms of human computation: micro-labor markets and games-with-a-purpose. They show that for this task human computation beats automation, and that games yield better results than micro-labor markets.

This section next presents three papers suggesting directions for future applications of human computation. First, François Bry presents an approach to credit risk rating that turns not only to lenders but also debtors in assessing the risk faced in the market. Purvis and Hardas next propose a human computation perspective on innovation, formulating the network of people involved in innovation in a way that captures many of the social elements that people bring to bear within organized human labor. Finally, Brambilla and Fraternali present a human computation perspective to integrating social interaction and business process management, where social interactions are treated as extensions to business process models.

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The section concludes with Thomsen's provocative chapter that considers the application of human computation to "wicked problems"—tasks that are so difficult humans can't determine if a proposed solution will solve the task. His goal is nothing less than to seek the creation of human computation systems that solve problems that could not otherwise be previously solved. His chapter discusses the various characteristics that will be necessary to build applications capable of tackling wicked problems with human computation.

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